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SYSTEMATIC CONTROL AND APPLICATION FOR 7 DOF UPPER-LIMB EXOSKELETON

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SYSTEMATIC CONTROL AND APPLICATION FOR 7 DOF UPPER-LIMB EXOSKELETON

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

DOCTOR OF PHILOSOPHY

in

DEPARTMENT OF ELECTRICAL ENGINEERING

by

Hyunchul Kim

March 2012

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Abstract

Systematic Control and Application for 7 DOF Upper-Limb Exoskeleton

by

Hyunchul Kim

The human arm including the shoulder, elbow, wrist joints and exclusion scapular motion has seven degrees of freedom (DOF) while positioning the wrist in space and orientating the palm is a task that requires six DOF. Given the redundant nature of the arm which has one more DOF than is needed to complete the task, multiple arm configurations can be used to complete a task based on none unique solution for the inverse kinematics. Despite this mathematical difficulty, the human motor control provides an unique solution for the arm redundancy as the arm moves in space. Resolving this redundancy is becoming critical as the human interacts with a wearable robotic system (exoskeleton) which includes the same redundancy as the human arm. Therefore, the inverse kinematics solution resolving the redundancy of these two coupled systems must be identical in order to guarantee a seamless integration.

Creating a proper control scheme between a wearable robot and human arm starts from an understanding of the redundant nature of the human arm. The redundancy of the arm can be formulated kinematically by defining the swivel angle - the rotation angle of the plane including the upper and lower arm around a virtual axis connecting the shoulder and wrist joints fixed in space. Then a global exoskeleton robot control scheme targeted for the natural human robot interaction will be achieved by providing a robot with the precise swivel angle estimation for the given kinematic and dynamic states of the human arm. In order for this, we first study
human motor control mechanism for the simple reaching and grasping tasks from a kinematic point of view. Analyzing reaching tasks recorded with a motion capture system indicates that the swivel angle, which defines the redundancy of the human arm, is selected such that when the elbow joint is flexed, the palm moves toward the head for any wrist position. Based on these experimental results, a new criterion to resolve the human arm redundancy is formed and this criterion is to maximize the projection of the longest principle axis of the manipulability ellipsoid for the human arm on the vector connecting the wrist and the virtual target on the head region. For more realistic and natural human arm movement, we additionally considered the redundancy based on the dynamic criterion which minimizes the mechanical work done in the joint space for each two consecutive points along the task space trajectory. The swivel angles from the kinematic and dynamic criteria were linearly combined with different weight factors for the unified swivel angle. Post processing of experimental data collected with a motion capturing system indicated that by using the proposed synthesis of redundancy resolution criteria, the error between the predicted swivel angle and the actual swivel angle adopted by the motor control system was less than five degrees. This result outperformed the prediction based on a single criteria and showed that the kinematic constraint is dominant in a simple reaching and grasping tasks that frequently occurs in our daily life. In order to define the redundancy resolution mechanism for more generalized human arm movement, the effect of the wrist orientation on the redundancy of the human arm was superimposed onto the wrist position based swivel angle estimation. By applying the above inverse kinematics mechanism mimicking the natural human arm movement to the wearable robot, wearer can expect the synchronized movement with robot for unconstrained natural human arm movements. Finally, to accommodate
the unnatural movement pattern such as avoiding obstacle, purely reactive task space admittance control based on multiple force sensors is combined with the above control schemes for a global exoskeleton robot control scheme. Five subjects performed a peg in hole task for three different target locations to verify the performance of the proposed control scheme. The velocities and interaction forces at the upper arm, lower arm, handle and tip were recorded during the experiments. Power exchange between the subject and device was calculated for performance evaluation. Result shows that proposed control scheme outperforms purely reactive task space admittance control with energy exchange lowered by 11.22%.

Based on the proposed exoskeleton control scheme, the exoskeleton robot is applied to the stroke patient rehabilitation research project as a clinical trial. In order for this, 3-D video games directly interacting with the robotic system were designed and the assistive force mechanism for the patients was implemented in the exoskeleton robot. In addition a new metric called instantaneous efficiency (IE) was established to evaluate the therapeutic improvement. This metric is designed to reveal the degree of patient’s improvement in terms of natural human arm movements by looking at the joint angle configuration, speed and frequency of using uncomfortable joints comprehensively. As their movements are getting closer to the natural human arm movement of normal people, the IE index increases. Ten subjects participated in this pilot research project either as an unilateral or a bilateral therapy group for six weeks. Results shows that even in a short six weeks rehabilitation program, patients’ Fugl-Meyer scores as well as the efficiency index of the movements were significantly improved.
Acknowledgments

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*Veni, Vidi, Vici*

*-Julius Caesar-*
Part I

First Part
Chapter 1

Introduction

Synergy between human arms and wearable robot systems (E.g. the exoskeletons) enables robots to boost and assist physical capability of the human. In particular, assistive wearable robotic systems may improve the rehabilitation treatment as well as the quality of life of patients suffering from a wide spectrum of neuromuscular disorders such as stroke, spinal cord injury, and muscular dystrophy[92, 90, 65, 118, 38]. However, the physical coupling between a wearable robot and the human body imposes many challenges for creating stable and natural integration between two systems. Due to this reason, the ultimate goal toward the wearable robot control is to increase the transparency of the human-robot interface so that the operator feels less reaction from the wearable robot[99, 28]. In other words, their motor control mechanism must co-exist to recover and maintain identical movements.

The human arm is the one among many redundant sub-systems of the body. With its shoulder, elbow and wrist joints (excluding scapular motion) it has seven DOF while positioning of the wrist in space and orientating the palm is a task that requires only six DOF. As such,
the human arm includes one additional DOF than is needed to complete the task. Given the re-
dundant nature of the arm, multiple arm configurations are possible to complete a task, which is
expressed mathematically by none unique solution for the inverse kinematics. Since the inverse
kinematics solution resolving the redundancy of these two coupled systems must be identical to
guarantee a seamless integration[92, 97], it is important to understand the mechanism of human
arm motor control and formulate an unique solution for the arm redundancy as the arm is moved
in space.

In this chapter, we briefly summarize the history[17] of the powered exoskeleton
which enabled the human-robot interaction in various application area such as neural reha-
bilitation and introduce the research result for the human motor control mechanism as a viable
control scheme for the exoskeleton robot.

1.1 Wearable Robot Systems

Over the past several decades, a number of important research efforts have resulted
in an improved synergy between wearable robot systems and their human users, either by im-
proving the mechanical design of the wearable robots or by improving the underlying human
machine interface (HMI).
1.1.1 Early Generation Exoskeleton

1.1.1.1 Hardiman

The first generation of the wearable exoskeleton robot, known as Hardiman[Fig. 1.1(a)1.1(b)] hydraulically powered machine (680 kg, thirty DOF), was developed by General Electric Research in cooperation with researchers at Cornell University and with financial support from the U.S. Office of Naval Research for power augmentation[13, 12, 76]. The Hardiman was a full body type exoskeleton robot that has two joints for hand, seven joints for arm, four joints for leg and two joints for foot in its left or right side of the robot. The control mechanism adopted to Hardiman was Hydromechanical Rate Control with Force Feedback for the hand, Electrohydraulic Bilateral Servo Control with Force Feedback Ratio 25:1 and Electrohydraulic Unilateral Servo with Indirect Force Feedback for Leg (including Foot). However the unsatisfactory performance in the responsiveness, controllability and stability resulted in a violent
Figure 1.2: Early generation exoskeleton: a) Berkeley lower extremity exoskeleton for soldier and b) Berkeley Bionics’ eLEGS exoskeleton for patients suffering neuromuscular disease.

motion and as a result the exoskeleton could not be worn by a person. Although the Hardiman project showed unsatisfactory research in terms of the performance, it identified many challenging and important research issues that should be resolved for more stable and natural human-robot interaction.

1.1.1.2 BLEEX

The second generation of exoskeletons focused on the advanced control scheme for the constructive human-robot interaction such as force signals that could reflect the human’s intention on the robot at the dynamic level. This improvement in control strategy enabled the operators to have full physical contact with the exoskeleton during manipulation [119, 59, 60]. The Berkeley Lower Extremity Exoskeleton (BLEEX) in Fig. 1.2(a), one of the most successful and visible exoskeletons from the DARPA projects, is energetically autonomous which means
it carries its own power source. The kinematics and actuation scheme of the exoskeleton were designed by considering a behaviour of a human gait analysis data[59, 60]. In order to achieve the energetically autonomous characteristic as a core technology of the BLEEK, significant effort was made to develop a hybrid hydraulic/electric portable power supply[60]. In order to increase the sensitivity of the lower limb exoskeleton to the pilot’s forces and torques, BLEEX mainly exploit the sensory information from the exoskeleton and minimize the information between the exoskeleton and the pilot (wearer). From the success of the BLEEX, a UC Berkeley spin-off, currently EKSO[24], launched a lower limb exoskeleton eLEGS[Fig. 1.2(b)] which enables people with paralysis to stand up and walk. This rehabilitation exoskeleton is battery-operated and untethered. Currently it is used under medical supervision for rehabilitation and training.

1.1.1.3 SARCOS exoskeleton

The Sarcos Research Corporation also has developed a full-body type exoskeleton robot[Fig. 1.3(a)1.3(b)] targeted for the energetically autonomous robot. The early stage of Sarcos exoskeleton robotic research has been launched by DARPA EHPA(Exoskeletons for Human Performance Augmentation) program. The Sarcos exoskeleton has each joint of the system powered by the rotary hydraulic actuators[43, 17] and utilizes force sensors between the robot and the wearer for the admittance control widely used for the human power augmentation. Reportedly the Sarcos exoskeleton can support structure upto 84 kg, stand on one leg while carrying another person on its back, walk at 1.6 m/s while carrying 68 kg on the back and 23 kg on the arms and can also provide complicated movement such as twisting, squatting, and
Figure 1.3: Early generation exoskeleton: a) Sarcos full body exoskeleton and b) Sarcos exoskeleton demonstrating breaking boards

kneeling[43, 17]. However, the applied control scheme to Sarcos robot does not allow full synchronization with the human motion due to the purely reactive admittance control scheme.

1.1.2 Exoskeleton for the Robotic Rehabilitation

Another important and vividly researched area for the wearable robot is medical rehabilitation and impairment assistance. MIT-MANUS[65, 42, 64] is possibly one of the most successful rehabilitation robot and widely used in many clinical research[Fig. 1.4(b)]. Currently there are four types of MANUS considering the patients impairment types[64]which are planar 2-DOF active module, vertical 1-DOF active module, wrist 3-DOF active module and 1-DOF passive grasp module. Considering the safe, stable and compliant operation for the patient suffering neuromuscular diseases [65], MANUS adopted backdrivable hardware and impedance control as distinguishing features of the robot control system such that it allows patients actively
involved in the physical therapy[65, 42, 64]. In spite of the successful work of the professor Hogan and his team in MIT who designed MIT-MANUS, MANUS is not an wearable exoskeleton robot that can fully interact with human in an entire workspace. Due to this limitation of the MANUS, its application area is limited and the objective assessment for therapeutic improvement is not considered. Thus many researchers started to work on a rehabilitation robotic system based on exoskeleton robot to fully exploit the advantage of the robot assisted rehabilitation. In the following section we introduce well known exoskeleton type robots for the patients suffering neuromuscular disease [65].

1.1.2.1 HAL-5

HAL(Hybrid Assistive Limb)-5 is the one developed by Prof. Yoshikuyi Sankai and his team at the University of Tsukuba, Japan for more general and commercial exoskeleton robotic systems. HAL-5 is a full body exoskeleton robot for the purpose of human augmentation and powered by the DC motors at the shoulder, elbow, hip and Knee joints. Unlike the
Figure 1.5: Rehabilitation robotic system: a) ARMIN developed in ETH, Swiss and b) Pneu-WREX developed in UC Irvine, USA

previously mentioned exoskeleton robots, the most distinguishing feature of HAL-5 is that the motion controller utilizes the skin-surface electromyographic (EMG) electrodes placed on the hip and knee area of the wearer’s body together with potentiometers for joint angle measurement, ground reaction force sensors, gyroscope and accelerometer. Though the EMG signal quality is not good enough for the sophisticated motion prediction, it enables the faster user intent detection compared to the purely reactive admittance control based on the force sensors. Due to the biological difference between users, it is known that control parameters of HAL-5 should be adapted to the individual users for the optimal operation and it takes two months[25].

1.1.2.2 ARMin

ARMin[Fig. 1.5(a)] is an exoskeleton developed in ETH Zurich and University Zurich. There are several prototypes of ARMin developed and it has seven DOF since the second prototypes[89, 90, 88]. Three DOF of the shoulder joint is for flexion/extension in the sagittal plane, abduction/adduction in the frontal plane and an arm elevation actuation for the vertical
movement of the robot arm to comply with the natural movement of the wearer’s upper arm. The four DOF at the distal part of the robot takes care of arm internal/external rotation, elbow flexion/extension, forearm pronation/supination, and wrist flexion/extension[89, 90, 88]. The wrist ulnar/radial deviation is constrained in a neutral position to reduce the complexity of the device. The technologies from ARMin is commercialized in the Hocoma company as the first commercialized robotic arm exoskeleton in the world. This robot also provides a visual, acoustic and haptic interfaces together with cooperative control strategies to facilitate the patient’s active participation in the game. In addition, the length of the upper arm, the lower arm, the hand and the height of the device is adjustable for the different size of patients. For an easy access to the rehabilitation site and robotic system, patients can approach to the system sitting on an wheel chair. While the mechanical structure of the ARMin robot is carefully designed, the robot has a simple passive gravity compensation schemes and only supports unilateral type of therapy due to it’s single arm structure[89, 90, 88].

1.1.2.3 Pneu-WREX

The original WREX(Wilmington Robotic Exoskeleton) was developed for children with arm weakness caused by a debilitative condition as a passive, mobile arm support. Professor James Bobrow in UC Irvine and his team extended this passive device to a six DOF robotic WREX named Pneu-WREX[Fig. 1.5(b)]which uses pneumatic actuators[112, 93, 111]. Although the pneumatic actuator is hard to control due to its non-linear characteristic, it produces relatively large forces with a low on-board weight[75]. Thus Pneu-WREX adopted pneumatic actuators to power up each joint with light weight. The robot interact with virtual-reality game,
Figure 1.6: RUPERT (Robotic Upper Extremity Repetitive Therapy) developed in Arizona State University researchers team led by Dr. Jiping He

T-WREX based on a Java Therapy 2.0 software system[111]. The game is mainly focused on simple tasks such as reaching for items on shelves, washing a stove, eating, washing the contralateral arm, and picking up eggs and breaking them over a pan. Another distinguishing feature of this robot is assist-as-needed control scheme[112, 93, 111]. In this adaptive control scheme, control detects patient’s intention such that only the smallest amount assist is applied to the patient for the intensive engagement in the therapy. However, due to the fundamental limitation of six DOF robotic system, it does not utilize the redundant nature of the human arm movement and potentially this might result in the inadequate rehabilitation result.

1.1.2.4 RUPERT

Arizona State University researchers team led by Dr. Jiping He developed a robotic arm, RUPERT (Robotic Upper Extremity Repetitive Therapy) targeted for the cost-effective and light weight stroke patient rehabilitation[41, 40]. There are couple of prototypes designed so far. The earlier version, RUPERT I and RUPERT II adopted four pneumatic muscles to
assist repetitive movement at the shoulder, elbow and wrist with adjustable mechanical arm structure to accommodate different arm lengths and body sizes. The device provides the patient with assisting force to facilitate the fluid and natural arm movement essential for the normal daily life such as reaching for objects or feeding themselves. The controller for the pneumatic muscles can be programmed for repetitive exercises to the specific user that improve arm/hand flexibility and strength[41, 40]. Since the system is targeted for the low cost and light weight device, the rehabilitation program is restricted to the traditional repetitive movement training and it lacks the interaction with virtual reality environment.

1.1.2.5 UL-EXO7

UL-EXO7[52, 91, 92, 97] is a seven DOF exoskeleton robot developed by professor Jacob Rosen and his research team in UC Santa Cruz[Fig. 1.7(a)]. The mechanical design of the robot is based on the kinematics and dynamics of the human arm during activities of daily living(ADL) such that it supports 97% of the human arm workspace[52, 92, 91]. Articulation of the exoskeleton is achieved by seven single-axis revolute joints[Fig. 1.7(b)] which support 99% of the range of motion required to perform daily activities[92]. In addition, rotating the first joint by 47.5 degrees around the x axis(right direction with respect to the right shoulder), 53.6 degrees around the y axis(frontal direction with respect to the right shoulder), and making joints two and three orthogonal to their preceding joint, the singularity in the shoulder can be located outside of the human arm workspace during ADL. Three revolute joints are responsible for shoulder abduction-adduction, flexion-extension and internal-external rotation. A single rotational joint is employed at the elbow, creating elbow flexion-extension. Finally, the lower arm
and hand are connected by a three-axis spherical joint resulting in wrist pronation-supination, flexion-extension, and radial-ulnar deviation. As a human-machine interface (HMI), four six-axis force/torque sensors (ATI Industrial Automation, model-Mini40) are attached to the upper arm, the lower arm, the hand and the tip of the exoskeleton [83]. The force/torque sensor at the tip of the exoskeleton allows measurement of interactions between the exoskeleton and the environment. As a background control scheme, it has a feedforward active gravity compensation, friction compensation, swivel angle estimation[62] and an optional admittance control based on force/torque sensors[83]. There are specially designed 3-D video games for the stroke patient rehabilitation based on Microsoft Robotic Developer Studio 2008[1] such that it can interact with the virtual reality[Fig. 1.7(c)].

1.2 Previous Work on the Exoskeleton Control

Since the exoskeleton robot is directly interacting with human, it is important for the exoskeleton controller to provide the comfortable and synchronized movement with the
operator. The basic and ideal control strategy is to estimate the desired joint angles for the given end effector position and orientation by solving the inverse kinematics of the human arm. However it is known that the inverse kinematic solution for the human arm as a redundant manipulator is not uniquely defined and requires additional constraints such as minimum energy or joint torque constraints. In this section, we summarize the well known redundancy resolution algorithms.

1.2.1 Pseudoinverse Jacobian

The position of the end effector $X = [x_1, x_2, \ldots, x_m]^T \in \mathbb{R}^m$ in an $n$-link robot manipulator is represented as a function of joint space variables $\theta = [\theta_1, \theta_2, \ldots, \theta_n] \in \mathbb{R}^n$ as follows.

$$X = f(\theta)$$ (1.1)

where $f$ denotes the forward kinematic function. The goal of the inverse kinematics is to define the corresponding joint variable $\theta$ at a specific end effector position $X$. For a redundant robot manipulator ($n > m$), sophisticated manipulator control such as obstacle avoidance, fault tolerance or singularity avoidance is possible. However due to the extra degrees of freedom, there is no longer an unique configuration of joint angles for the given end effector position and the inverse kinematic problem is non trivial. There are several methods for inverse kinematic solutions; among them, the Jacobian pseudoinverse is widely used as a general approach to solve the inverse kinematic problems at the velocity level. In this approach, the transformation between end-effector and joint velocity is achieved by differentiating Eq. 1.1 with respect to time.

$$\dot{X} = J \dot{\theta} \left( \dot{X} = \frac{dX}{dt}, \dot{\theta} = \frac{d\theta}{dt} \right)$$ (1.2)
where $J$ is the Jacobian, which is a function of $\theta$. For a small time interval, $J$ can be considered constant over the interval of the displacement and the finite displacement between $\delta \theta$ and $\delta X$ can be approximated as $\delta X \approx J \delta \theta$. Then the general solution to Eq. 1.2 is given by

$$\dot{\theta} = J^+ \dot{X} + (J^+ J - I_n) z$$

(1.3)

where $J^+$ is the pseudo-inverse matrix of $J$, $I_n$ is the $n \times n$ identity matrix and $z$ is an arbitrary matrix. Note that $J^+$ in the under determined case is defined as $J^+ = J^T (JJ^T)^{-1}$. In Eq. 1.3, $J^+ \dot{X}$ and $(J^+ J - I_n) z$ is the minimum norm solution and homogeneous solution of Eq. 1.2.

When the homogeneous part is plugged into the Eq. 1.2, we have

$$\dot{\theta} = (J^+ J - I_n) z \rightarrow \dot{X} = J \dot{\theta}$$

(1.4)

$$\dot{X} = J (J^+ J - I_n) z$$

(1.5)

$$X = (JJ^+ J - J) z$$

(1.6)

$$\dot{X} = (J - J) z$$

(1.7)

$$X = 0$$

(1.8)

The Eq. 1.4 implies that $(J^+ J - I_n)$ in the right side of the Eq. 1.3 is the operator that projects any vector $z$ into the null space of the jacobian matrix $J$. The homogeneous solution enables different joint configuration without affecting the end effector position. Thus by applying the proper cost function to $z$ as a secondary criterion for Eq. 1.2, specific tasks such as obstacle avoidance can be achieved while at the same time tracking the given end-effector trajectory as a primary goal[72, 87, 74].


1.2.2 Posture-based Redundancy Resolution

The inverse kinematic solution of the wearable robot is closely related to the human motor control. Thus there has been many efforts to understand the human motor control strategies by considering the various biological aspect of the human. So far the redundancy resolution of the human motor system is not fully understood. It is widely known that multiple strategies should be combined together to explain the human motor control.[2].

1.2.2.1 The Donder’s law

The original Donders law[18] states that the central nervous system (CNS) uses an unique orientation of the eye for each gaze direction. An extension of the Donder’s law[18][2] further shows that the original Donders law can be applied to the upper arm for each position of the hand. Thus the orientation of the upper arm during pointing is represented as a rotation angle around a rotation axis from a reference position to the current position which is defined by

\[
\vec{r} = \tan\left(\frac{\alpha}{2}\right)\vec{n}
\]

where \(\vec{n}\) means the unit vector of the rotation axis and \(\alpha\) is the angle of rotation along that axis[37, 104]. The three orthogonal components of rotation vector \(\vec{r} (r_u, r_v, r_w)\) represent the torsional, elevation, and azimuth components, respectively. The relation between torsion angle \(\zeta\) and the torsional component \(r_u\) is governed by Eq. 1.9, where \(\vec{r}\) equals \(r_u\) when \(\vec{r}\) is along the humeral axis of the upper arm and \(\alpha = \zeta[18, 2]\). According to the assumption in Donders law, torsion is fully specified by azimuth and the elevation of the upper arm while pointing at
the target location such that a polynomial fit can find out the torsional component \( r_u \) in terms or \( r_v \) and \( r_w \)[31, 32]. The Donders’ law is also known to be valid for other parts of human body such as the head in addition to the eyes and the arms. Note that many of the different body parts are governed by the same biological law regardless of the different biomechanics. The eyes close to a sphere shape move with a minimum number of orthogonally arranged muscles and consequently have a negligible inertia while a head and arms have considerably high inertia with more sophisticated muscular structure. Coincidently the motion strategies for controlling body parts of different morphology, kinematics and dynamics follow the similar biological laws.

1.2.2.2 The Fitts’ law

Fitts’s law (often cited as Fitts’ law)[27] describes a pointing motion of a human arm primarily used in human-computer interaction and ergonomics. This law states that the accuracy of the pointing motion decreases as the speed of pointing motion increases. The mathematical representation of the Fitts’s law can be formulated in several different ways and one of the most well known form is from the extension of ShannonHartley theorem[101, 36] as follows

\[
T = a + b \log \left( 1 + \frac{D}{W} \right)
\]

(1.10)

where \( T \) is the average time for completing the movement task, \( a \) represents the start/stop time of the device, \( b \) stands for the inherent speed of the device which can be determined experimentally, \( D \) is the distance from the starting point to the center of the target and \( W \) is the width of the target reflecting the accuracy of the motions. Note that the constant ’1’ in the log of Eq. 1.10 can be varied depending on the variation of Fitts’ law.
As a result, this law describes the trade-off between the motion speed and motion accuracy. The time required to rapidly move to a target area is a function of the distance to the target and the size of the target.

1.2.3 Dynamic constraint

Dynamic is an important part of the human arm movement. Thus it can be hypothesized that the movement of the human arm results from the optimization process of the dynamical constraint as well as the other kinematic constraint. In this line of research, Soechting and colleagues proposed that the deviations of Donders law could be explained by assuming that movements are made based on the minimization of work criteria\[67, 102\]. According to this hypothesis, the dynamics and kinematics are tightly coupled based on the optimization criterion, given the movement time with the initial and final position of the movement. The minimum-torque-change model\[108\] also explains the human arm kinematic in terms of dynamical constraints.

1.2.3.1 Minimum work model

The minimum work model was first introduced by Soechting and colleagues\[67, 102\]. For the elbow and the shoulder joints defining the posture of the arm in the space, the amount of the work $W$ necessary to move the arm from one point to another is defined as

$$W = \int \vec{T} \cdot d\vec{\Theta} \quad \text{(1.11)}$$

where $\vec{T}$ is the torque vector for the shoulder and elbow, and $\vec{\Theta}$ is the vector with joint angles in the shoulder and elbow. Ignoring gravitational forces, the amount of work done at time $t$ is
defined as the difference between kinetic energies at the position of time $t$ and starting position. Because the arm starts from rest, its kinetic energy at the starting position is zero. Therefore, work at some time $t$ can be written as

$$W = \int \vec{T} \cdot d\vec{\Theta} = \sum_{i=1,2} \left[ \frac{1}{2} m_i \vec{\nu}_i^T \cdot \vec{\nu}_i + \frac{1}{2} \vec{\Omega}_i \cdot I_i \cdot \vec{\Omega}_i \right]$$

(1.12)

In Eq. 1.12, parameter $i = 1, 2$ means two arm segments, forearm and upper arm. $\vec{\Omega}_i = d\Theta_i/dt$ and $m_i$ is the total mass of either upper arm or forearm, $\vec{\nu}_i$ is the speed of the arm segments at the center of mass and $I_i$ is the inertia tensor of the arm. Ignoring the gravity of the human arm, the total amount of work done during the movement becomes zero because the final velocity is zero. This is because the amount of work done to accelerate the arm is cancelled out by the work required to decelerate the arm at the end of the movement. Assuming that the movement velocities are bell shaped during the arm movement and that joint velocities in elbow and shoulder reach a peak value simultaneously, the amount of work is maximum at the time of peak velocity[55]. The work related to this peak value of kinetic energy is used as a cost function for the minimization of work to define the redundancy of the human arm.

### 1.2.3.2 Minimum torque model

Another line of well known dynamical constraint is minimum-torque-change model. Similarly from the minimum work model in the previous section, different type of the cost function is established by considering the amount of torque required to fulfil the hand movement. Uno et al.[108] proposed that the human arm movement in the 3-D space can be described by solving the following cost function.
\[ C_T = \frac{1}{2} \int_{t_0}^{t_n} \sum_{i=1}^{N} \left( \frac{dT_i}{dt} \right)^2 \, dt \]  

(1.13)

where \( T_i \) is the torque generated by the \( i \)th joint. The individual torque \( T_i \) can be evaluated by the following Lagrange formulation.

\[ \vec{T} = d \left( \frac{\partial L}{\partial \dot{\vec{q}}} \right) - \frac{\partial L}{\partial \vec{q}} \]  

(1.14)

where \( \vec{q} \) means the joint angle vector and \( L \) is defined as follows.

\[ L(\vec{q}, \dot{\vec{q}}, t) = K(\vec{q}, \dot{\vec{q}}, t) - V(\vec{q}) \]  

(1.15)

with \( K \) the kinetic energy and \( V \) the potential energy. The gravity and the potential energy of motion is set zero to find out the optimum solution that can minimize Eq. 1.13.

### 1.2.4 Biomimetic approach

Several criteria such as posture-based control \[31, 32\], minimum mechanical work \[102, 55\] and minimum torque change \[108, 69\] were previously introduced aiming to resolve the human arm redundancy. However the cost functions proposed to model motion principles of human arm movement are quite complex to be used for the realtime inverse kinematics solution of wearable robots and requires the combination of multiple constraints to achieve more realistic human motion. For much simpler and feasible inverse kinematic solution for the human-machine interface, people started to research the law for biomimetic trajectory planning of human and its application to the robot inverse kinematics\[5, 4\]. Towards this goal, dependen-
Recent work in [4] presented a biomimetic approach to solve the inverse kinematics for a redundant robot arm. In this work, the dependencies among the human joint angles are studied using a Bayesian network model[39, 4]. An objective function based on this model is used as a closed-loop inverse kinematic algorithm for a redundant robot arm. Using this algorithm, the end-effector of the robot arm can be positioned in the three dimensional (3D) space using human-like joint configurations with reduced computational complexity compared to the conventional algorithms introduced in the previous sections. Fig. 1.8 shows the prediction result of the proposed biomimetic approach in comparison with the inverse kinematic solution of the conventional redundancy resolution scheme[4]. As the conventional inverse kinematic algorithm in Fig. 1.8, the jacobian pseudoinverse method described in Section. 1.2.1 with joint
limit and singularity avoidance as the second criteria was adopted for comparison.

In general the system identification-based approach directly models the human motor function by observing the joint angles and the end effector position. This kind of approach is somewhat intuitive and can create the human-like motion with reasonable computation complexity. However, it requires that modelling the human motor function should be precise for the stable inverse kinematic problem and its possible application to the wearable robot due to the safety issue. If the system identification model parameters does not converge to right values due to the insufficient training data sets or the imperfect learning algorithm, the system output will not guarantee the reasonable decoding of the joint angles[39, 66].

1.3 Contributions and organization

So far we have investigated the various algorithms to resolve the redundancy of the human arm for the natural human-robot interface. The criteria for redundancy resolution introduced above are subject to the following main deficiency: (1) high level of computational complexity for the real time operation in a wearable robotic system, (2) numerical instability resulting from the nature of ill-posed inverse kinematic problems in the redundant manipulator, (3) deficiency of physical and biological interpretation for the human arm movement mechanism, (4) excluded wrist orientation effect on the redundancy of the human arm and (5) deficiency of structured control strategy that can cope with both structured and unstructured human arm movements.

Therefore the reported work in this thesis is focused on improving the deficiency
described above. First, the redundancy of the arm is expressed mathematically by defining the swivel angle: the rotation angle of the plane including the upper and lower arm around a virtual axis connecting the shoulder and wrist joints which are fixed in space. Then a new redundancy resolution criterion in the kinematic level was developed by studying human arm kinematic data under the controlled experiment protocol[62]. The proposed kinematic criterion is defined by carefully observing the functional difference between the conventional robot and human. According to this criterion, the redundancy of the human arm movement is defined such that the manipulability of the human arm during the natural reaching task is maximized on the directional vector connecting the wrist and the virtual target on the head region, which includes all the important sensory organs. The proposed new criteria provides the closed form solution of human arm inverse kinematic for the given wrist position and orientation, which is numerically stable and computationally efficient.

Since moving the human arm with mass and velocity is governed by the human arm dynamic equation, it is important to find out the dynamic effect on the redundancy resolution of the human arm. In order for this, the final form of swivel angle is represented as the linear combination of swivel angles based on the proposed kinematic and dynamic constraint with different weighting factors. By looking at the ratio of two weighting factors, the dynamic aspect of the human arm movements can be revealed. Among many, the mechanical work done in the joint space for each two consecutive points along the task space trajectory is adopted as a cost function and the swivel angle from this dynamic criterion is determined by minimizing the given cost function[55]. The performance of the combined redundancy resolution scheme is thoroughly examined by analyzing the kinematic data collected from the motion capture
For the practical implementation in the exoskeleton robot, it is necessary to have a control scheme that can embrace the unnatural movement such as avoiding obstacles. In order for this, the force interaction between the wearable robot and the user is extracted via force sensors on the wearable robot and translated into the velocity in the joint space based on the admittance control. By combining the admittance control scheme with the newly defined inverse kinematic criterion, the global robot control scheme is established and exoskeleton can render more flexible human arm movements. Then the proposed global control scheme is compared to a purely reactive admittance controller by the performance on a peg-in-hole task.

Finally, the proposed redundancy resolution algorithm is applied to the exoskeleton robot and tested in the stroke patient rehabilitation study. In this study, total of 10 subjects were tested under the unilateral and bilateral movement type therapy which require different combination of assistive forces from the exoskeleton robot. In order for this, various 3-D video games interacting with exoskeleton robot as well as data recording systems were developed using the Microsoft Robotic Development Studio and matlab program respectively. All the joint and force information recorded during the therapy were analyzed to provide the therapist with more objective assessment metric that can compensate the conventional assessment metrics.
Part II

Second Part
Chapter 2

Human arm model and Exoskeleton(UL-EXO7) system

2.1 Human arm model

The kinematics and dynamics of the human arm during activities of daily living were previously studied in order to determine the specifications for the exoskeleton robot shown in Fig. 3.1(a)[92, 52]. The upper limb of the human is composed of segments linked by articulations with multiple degrees of freedom. It is a complex structure that is made up of both rigid bone and soft tissue. This soft tissue moves and slides relative to the bone during movements and interactions with the environment. Additionally, muscle contractions cause changes to their shape and the overall stiffness of the arm. Although it is hard to mathematically model the complex soft tissue, the overall arm movement can be represented by a much simpler model composed of rigid links connected by joints. Three rigid segments, consisting of the upper arm,
lower arm and hand, connected by frictionless joints, make up the simplified model of the human arm. By placing a reference frame at the shoulder, the upper arm and torso are rigidly attached by a ball and socket joint. This joint is responsible for shoulder abduction-adduction (abd-add), shoulder flexion-extension (flx-ext) and shoulder internal-external (int-ext) rotation. The upper and lower arm segments are attached by a single rotational joint at the elbow, creating elbow flx-ext. Finally, the lower arm and hand are connected by a three axis spherical joint resulting in pronation-supination (pron-sup), wrist flx-ext, and wrist radial-ulnar (rad-uln) deviation. Ko-rein [63] was one of the first to study this seven DOF model. Since then, many other researches have used this seven DOF model to study human arm movement for computer graphics [53, 69], redundant robots[44], upper limb exoskeletons[91, 92, 97, 107], biomechanics [110, 117, 114] and much more. This model does neglects translational and rotational motion of the scapula and clavicle. For this reason, others have used five [16] or even seven DOF [77] models of the shoulder, resulting in nine and eleven DOF models of the arm. The seven DOF model gives a good combination of motion accuracy while reducing the model complexity. This model of the arm is a redundant model. Knowing the position and orientation of the hand is not enough to fully define the configuration of the arm, an additional constraint is necessary to fully represent the joint angle configuration of the arm. Fig. 2.2(a) depicts the frame structure and rotation axis of each joint for the seven DOF arm model used in this paper.
2.2 Exoskeleton Design

The kinematics and dynamics of the human arm during activities of daily living (ADL) were studied in part to determine the engineering specifications for the exoskeleton design [Fig. 2.1] [91, 92]. Articulation of the exoskeleton is achieved about seven single axis revolute joints. One for each shoulder abd-add, shoulder flx-ext, shoulder int-ext rotation, elbow flx-ext, forearm pron-sup, wrist flx-ext, and wrist rad-uln deviation. The range of motion of the exoskeleton support 99% of the ranges of motion required to perform daily activities [92]. A result of representing the ball and socket joint of the shoulder as three intersecting joints, is the introduction of singularities not present in the human arm. A significant consideration in exoskeleton design is placement of singularities [92]. For the exoskeleton arm, singularities occur when joints 1 and 3, or joints 3 and 5 align. To minimize the frequency of this occurrence, the axis of joint 1 is positioned such that singularities with joint 3 takes place only at locations
that are anthropometrically hard to reach. With each of these singularity vectors at or near the edge of the human workspace, the middle and majority of the workspace is free of singularities [91, 92].

The human machine interface (HMI) consists of three attachment point on the exoskeleton[Fig. 2.1(a)]. One attachment point is for the upper arm, one is for the lower arm, and the last is for the hand. The hand HMI consists of a handle, the upper and lower arm HMIs consists of a pressure distributive structural pad that securely straps to the mid-distal portion of each respective arm segment. Each interface is rigidly attached to a six-axis force/torque sensor(ATI Industrial Automation, model - Mini 40) that is in turn rigidly attached to the exoskeleton. These sensors allow every force and torque interactions between the exoskeleton and the user to be measured. A forth force/torques sensor at the tip of the exoskeleton allows measurement interactions between the exoskeleton and the environment.

2.3 The Redundant Degree of Freedom and Swivel Angle

For a fixed position of the shoulder in space along with a given position and orientation of the wrist, the human arm configuration is fully defined if and only if the position of the elbow joint is fully specified. With its three joints, the arm forms a triangle with one corner at the shoulder joint \( P_s \), one corner at the elbow joint \( P_e \), and the last corner at the wrist joint \( P_w \) [Fig. 2.2(b)]. Both the shoulder and wrist joints are spherical joints allowing the rotation of point \( P_e \) around the vector \( (P_w - P_s) \) [Fig. 2.2(b)]. A local coordinate system allocated at the center of the elbow circle \( P_e \) with three orthogonal unit vectors \( (\tilde{n}, \tilde{u}, \tilde{v}) \) provides a reference
Figure 2.2: Kinematic model of the human arm and its associated coordinate systems: a) The global reference frame $F_G(x_G, y_G, z_G)$ defined on $P_s$ and joint angles $[\theta_1, \theta_2, \ldots, \theta_7]$ for seven DOF arm model in an initial position of the right arm. b) The extra degree of freedom defined by a rotation axis that goes from the shoulder to the wrist. c) A coordinate frame at the center of the elbow circle and the swivel angle allowing the parameterization of the elbow position by a single variable coordinate system to define and measure the swivel angle ($\phi$) of the elbow [Fig. 2.2(c)].

\[
\vec{n} = \frac{(P_w - P_s)}{|P_w - P_s|}, \quad \vec{u} = \frac{(\vec{a} - (\vec{a} \cdot \vec{n})\vec{n})}{|\vec{a} - (\vec{a} \cdot \vec{n})\vec{n}|}, \quad \vec{v} = \vec{n} \times \vec{u} \tag{2.1}
\]

Setting $\vec{u} = -z$ in Eq. 2.1 positions the elbow at its lowest point when $\phi = 0$ [6]. Given the geometry depicted in Fig. 2.2(b), the position of the elbow can be expressed as a function of $\phi$[106] such that

\[
R = U \sin(\alpha) \tag{2.2}
\]

\[
P_e = P_s + U \cos(\alpha) \cdot \vec{n} \tag{2.3}
\]

\[
\cos(\alpha) = \frac{U^2 - L^2 - ||P_w - P_s||^2}{-2L^2||P_w - P_s||} \tag{2.4}
\]
Where $U$ and $L$ are the length of the upper and lower arm segments respectively [Fig. 2.2(b)] and $\phi$ is defined as the swivel angle. Now the position of the elbow can now be expresses as a parametrization of $\phi$.

$$P_e = R[\cos(\phi)\vec{u} + \sin(\phi)\vec{v}] + P_c$$

(2.5)

It is also possible to represent $\phi$ with respect to $P_e$. First project $P_e - P_s$ onto the plane of the elbow circle based on $\vec{p}_e = [(P_e - P_s) - (\vec{n}\vec{n}^T)(P_e - P_s)]$. Then we can achieve the following expression

$$\phi = \text{atan2}[\vec{n}^T(\vec{u} \times \vec{p}_e), \vec{u}^T \vec{p}_e]$$

(2.6)

### 2.4 Kinematic Model and Exoskeleton Control Algorithm

The forward Kinematics transforms the position of the end effector $P_T \in \mathbb{R}^n$ in the local tool frame into $P_0 \in \mathbb{R}^n$ in the base coordinate system of a serially articulated $n$-links mechanism and describes $P_0 \in \mathbb{R}^n$ as a function of joint space variables $\theta = [\theta_1, \theta_2, \ldots, \theta_n] \in \mathbb{R}^n$ as shown in Eq. 2.7.

$$P_0 = g_d P_T = T_1 T_2 T_3 T_4 T_5 T_6 g_{st} P_T = T_1 T_2 T_3 T_4 T_5 T_6 T_7 P_T$$

(2.7)

where $T_i$ denotes the $4 \times 4$ homogeneous transformation matrix defining the rotation and translation with respect to the $i$th joint axis. Note that unlike the Denavit-Hartenberg parameter approach representing the relative motions of each link with respect to the previous link $g_{st}$ in Eq. 2.7, $g_{st}$ in Eq. 2.7 translates the end effector $P_T$ in the local tool frame to $P_T'$ in the global base frame based on the exponential coordinates system formulation approach\[86, 113]. Thus the homogeneous transformation matrix $T_i$ performs the rotations and translations around the
\( i \)th joint axis represented in the global base frame. There is not a simple one-to-one mapping between the exponential coordinates system and the Denavit-Hartenberg parameters approach but both have the same form of final transformation matrix \( g_d \) in 2.7. In this approach, \( T_i \) for rigid body motion is defined as

\[
T_i = \begin{bmatrix} R_i & P_i \\ 0 & 1 \end{bmatrix}
\]  \( (2.8) \)

where \( R_i \) is the 3 \( \times \) 3 rotation matrix about the axis \( \vec{\omega}_i \) and \( P_i \) equals to \( (P_{q_i} - R_i P_{q_i}) \), where \( P_{q_i} \) is a point that the \( i \)th axis of rotation passes through. For the arm model: \( \vec{\omega}_1 = [1, 0, 0]^T \), \( \vec{\omega}_2 = [0, 1, 0]^T \), \( \vec{\omega}_3 = [0, 0, 1]^T \), \( \vec{\omega}_4 = [1, 0, 0]^T \), \( \vec{\omega}_5 = [0, 1, 0]^T \), \( \vec{\omega}_6 = [1, 0, 0]^T \) and \( \vec{\omega}_7 = [0, 0, 1]^T \) and \( P_{q_{1,2,3}} = [0, 0, 0]^T \), \( P_{q_4} = P_{e_0} \), \( P_{q_{5,6,7}} = P_{w_0} \) with \( P_{e_0} = [0, 0, -U]^T \), \( P_{w_0} = [0, 0, -U - L]^T \).

### 2.5 Inverse Kinematics

The exoskeleton controller generates the desired joint angles for the given end effector position \( P_0 \in \mathbb{R}^m \) by solving the inverse kinematic problem of Eq.2.7.

### 2.6 Pseudoinverse Jacobian

One of the well known inverse kinematic solution for the redundant manipulator is based on the existing mapping between the joint velocity \( \dot{\theta} \) and the end effector velocity \( \dot{P}_0 \) through the Jacobian matrix \( J \), which is defined as \( \dot{P}_0 = J \dot{\theta} \). Given the redundancy nature of the system, the Jacobian pseudoinverse \( J^+ \) is used for solving the inverse kinematic problem[116].

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Then the general solution is given by

$$\dot{\theta} = J^+ \dot{P}_0 + (J^+ J - I_n) Z, \quad J^+ = J^T (J J^T)^{-1} \quad (2.9)$$

where $J^+$ is the pseudo-inverse matrix of $J$ for an under-determined (redundant) case ($n > m$), $I_n$ is the $n \times n$ identity matrix and $Z$ is an arbitrary vector. In Eq.2.9, $J^+ \dot{P}_0$ is the minimum norm and homogeneous solution of $\dot{P}_0 = J \dot{\theta}$. The term $(J^+ J - I_n) Z$ maps the null space on to itself which enables various joint configurations without affecting the end effector position and velocity. Thus by applying the proper cost function producing a specific $Z$ vector as a secondary criterion, specific arm postures can be achieved while, at the same time, tracking a given end-effector trajectory as a primary goal. One effective way of defining $Z$ vector is by using the objective function $H$ and project it onto the null space of the Jacobian through $(J^+ J - I_n)$. Then Eq.2.9 can be written as

$$\dot{\theta} = J^+ \dot{P}_0 + \alpha_w (J^+ J - I_n) \frac{\partial H(\theta, \theta_c(t))}{\partial \theta} \quad (2.10)$$

where $\alpha_w$ is a weighting parameter such that $\alpha_w > 0$. The following quadratic objective, called joint angle availability, was initially used for robotic manipulator in order to avoid joint limits [72].

$$H(\theta, \theta_c(t)) = \sum_{i=1}^{n} \left[ \frac{(\theta_i - \theta_{ci}(t))}{\Delta \theta_i} \right]^2 \quad (2.11)$$

$$\theta_c(t) = [\theta_{c1}(t), \theta_{c2}(t), \ldots, \theta_{cn}(t)]$$

where $\theta_i$ is the joint angle, $\Delta \theta_i$ is the operating range of the joint $i$ and $\theta_{ci}(t)$ is the desired joint angle of joint $i$. Utilizing Eq.2.11 in Eq.2.10 enables the joint configuration of a redundant
manipulator to remain close to $\theta_i(t)$. Assuming that the wrist orientation does not affect the human arm during a reaching task and the swivel angle is only affected by the wrist position, it is possible to match the configuration of the exoskeleton with the posture of the human arm by properly estimating the desired swivel angle $\phi$ which in turn defines the desired joint angles of the shoulder($\theta_{c1}(t)$, $\theta_{c2}(t)$ and $\theta_{c3}(t)$). Note that $\theta_{c4}(t)$ can be geometrically defined while $\theta_{c5}(t)$, $\theta_{c6}(t)$ and $\theta_{c7}(t)$ defining the orientation of the wrist joint can be determined by the operator or set as an initial value.

2.7 Analytic solution

Let’s rewrite the part of Eq 2.7 as follows.

$$T_1 T_2 T_3 T_4 T_5 T_6 T_7 g_{st} = g_d$$  \hspace{1cm} (2.12)

Eq 2.12 has seven unknowns and only six independent equations. To solve the inverse kinematics with a closed form function, an additional constraint must be imposed. The following function adds one additional independent equation when paired with Eq 2.12.

$$T_1 T_2 P_{e0} = P_e(\phi)$$  \hspace{1cm} (2.13)

Then the system is fully constrained based on Eq. 2.12 and Eq. 2.13. We will decompose Eq 2.12 and Eq 2.13 into one of two subproblems whose solutions are readily available.

2.7.1 Subproblem 1

Given the transformation matrix $T(\theta)$, Find $\theta$ such that:

$$T(\theta) P_0 = P_d$$  \hspace{1cm} (2.14)
This corresponds to rotating an initial point \( P_0 \) about a given axis until it is coincident with \( P_d \), the desired final position. The solution to this problem is:

\[
\theta = \text{atan2}[\vec{\omega}^T (\vec{u} \times \vec{v}), \vec{u}^T \vec{v}] \tag{2.15}
\]

\[
\vec{u} = (P_0 - P_r) - \vec{\omega} \vec{\omega}^T (P_0 - P_r) \tag{2.16}
\]

\[
\vec{v} = (P_d - P_r) - \vec{\omega} \vec{\omega}^T (P_d - P_r) \tag{2.17}
\]

where \( \vec{\omega} \) points in the direction of the rotation axis and \( P_r \) is a point the axis passes through. For the derivation refer to [86, 113]

### 2.7.2 Subproblem 2

Given the transformation matrix \( T_i(\theta_i)T_j(\theta_j) \) where the rotation axis of \( T_i \) and \( T_j \) intersect, find \( \theta_i \) and \( \theta_j \) such that:

\[
T_i(\theta_i)T_j(\theta_j)P_0 = P_d \tag{2.18}
\]

This corresponds to rotating an initial point \( P_0 \) about the rotation axis of \( T_j \) by \( \theta_j \) then about the rotation axis of \( T_i \) by \( \theta_i \), so that the final location of the point coincides with \( P_d \) the desired final position. The solution to this problem is found by first finding \( P_g \) as follows.

\[
P_g = \alpha \vec{\omega}_i + \beta \vec{\omega}_j \pm \sqrt{\gamma} (\vec{\omega}_i \times \vec{\omega}_j) + P_r \tag{2.19}
\]

\[
\alpha = \frac{(\vec{\omega}_i^T \vec{\omega}_j) \vec{\omega}_j^T (P_0 - P_r) - \vec{\omega}_i^T \vec{\omega}_i (P_d - P_r)}{(\vec{\omega}_i^T \vec{\omega}_j)^2 - 1} \tag{2.20}
\]

\[
\beta = \frac{(\vec{\omega}_i^T \vec{\omega}_j) \vec{\omega}_i^T (P_d - P_r) - \vec{\omega}_j^T \vec{\omega}_i (P_0 - P_r)}{(\vec{\omega}_i^T \vec{\omega}_j)^2 - 1} \tag{2.21}
\]

\[
\gamma = \frac{||P_0 - P_r||^2 - \alpha^2 - \beta^2 - 2 \alpha \beta \vec{\omega}_i^T \vec{\omega}_j}{||\vec{\omega}_i \times \vec{\omega}_j||^2} \tag{2.22}
\]
where $\vec{\omega}_i$ and $\vec{\omega}_j$ point in the direction of the rotation axes of $T_i$ and $T_j$ and $P_e$ is the point where the axes intersect. There may be zero, one or two real solutions for $P_g$ depending on $\gamma$. If solutions exist, then $\theta_i$ and $\theta_j$ can be found with subproblem one

$$T_i(-\theta_i)P_d = P_g$$
(2.23)

$$T_j(\theta_j)P_0 = P_g$$
(2.24)

For the derivation of this solution refer to [86, 113].

### 2.7.3 Decomposition of the Forward Kinematics

$\theta_4$ can easily be solved by an application of the law of cosine.

$$\theta_4 = \pi - \arccos \left( \frac{L^2 + U^2 - ||P_w - P_t||^2}{2LU} \right)$$
(2.25)

Eq. 2.13 is already in the form of Eq. 2.18 with $P_0 = P_{e_0}$ and $P_d = P_e(\phi)$, and an immediate solution for $\theta_1$ and $\theta_2$ is available. Note that Eq. 2.18 has two solutions. For a natural arm configuration the negative sign in Eq. 2.19 should be chosen.

Next to solve for $\theta_3$, Eq. 2.12 is premultiply by $(T_1T_2)^{-1}$ and then postmultiplied by $g_{st}^{-1}P_{w_1}$. Since $P_{w_1}$ is an eigenvector of $T_3$, $T_6$ and $T_7$ with eigenvalue one, $T_3T_6T_7P_{w_0} = P_{w_0}$. Then we have

$$T_3(T_4P_{w_0}) = (T_1T_2)^{-1}g_{st}^{-1}g_{st}^{-1}P_{w_0}$$
(2.26)

This is in the form of Eq. 2.14 when $P_0 = (T_4P_{w_0})$ and $P_d = (T_1T_2)^{-1}g_{st}^{-1}P_{w_1}$.

To solve for $\theta_5$ and $\theta_6$, Eq. 2.12 is premultiplied by $(T_1T_2T_3T_4)^{-1}$ and postmultiplied by $g_{st}^{-1}P_7$, where $P_7 = [1, 0, -U - L]^T$ is an eigenvector of $T_7$ with an eigenvalue of one. Then
we have $T_7P_7 = P_7$

$$T_5T_6P_7 = (T_1T_2T_3T_4)^{-1}g_dg_{st}^{-1}P_7 \quad (2.27)$$

This is now in the form of Eq. 2.18 when $P_0 = P_7$ and $P_d = (T_1T_2T_3T_4)^{-1}g_dg_{st}^{-1}P_7$. Eq. 2.18 has multiple solution and the negative sign in Eq.2.19 should be chosen.

Finally to solve for $\theta_7$, Eq. 2.12 is premultiplying by $(T_1T_2T_3T_4T_5)^{-1}P_s$ and then postmultiplied by $g_{st}^{-1}P_s$ as follows.

$$T_7P_s = (T_1T_2T_3T_4T_5)^{-1}g_dg_{st}^{-1}P_s \quad (2.28)$$

Eq. 2.28 is in the form of (2.14). Note that $P_0 = P_s$ and $P_d = (T_1T_2T_3T_4T_5)^{-1}g_dg_{st}^{-1}P_s$ in Eq. 2.14.
Chapter 3

Kinematics and dynamics of the human arm for the given end effector position

3.1 Swivel Angle Estimation based on a kinematic constraint

The human arm provided inspiration for the design of many of the industrial robotic arms in terms of joint configurations, link lengths and the ratio between them. Unlike the industrial robotic system that can be freely positioned and oriented with respect to their external environment, analyzing the human arm must be done in the context of the human body anatomy and in particular the sensory organs that affect the motion planning of the human arm. Among the many functions that the human arm is capable of, one of its primary function is to facilitate feeding and therefore the head is one of its primary targets. Moreover, given the role of the head as a cluster of sensing organs and the importance of the arm manipulation to deliver food to the mouth to sustain life, we hypothesized that
Figure 3.1: Arm Configuration: a) A human subject wearing two upper limb exoskeletons with seven degree of freedom each which support 95% of the workspace of the human arm. b) Graphical representation of the proposed redundancy resolution criteria indicating that for any given wrist position $P_W(t)$ at any given time $t_i$ there is a virtual destination $V_D(t_i)$ located at the subject’s head.

*The value of swivel angle selected by human motor control system to resolve the arm redundancy is selected to efficiently retract the palm to the head.*

It implies that during the arm movement toward an actual target, the virtual target point on the head is also set to efficiently retract the palm to the virtual target on the head at any time. The hypothesis can be described more formally by defining the virtual destination on the head as $P_m$ and hidden trajectory $V_D(t_i)$ to $P_m$ which is set up while the hand moves within the workspace of the arm as part of its reaching task[Fig.3.1(b)]. This hypothesis is supported by the intracortical stimulation experiments to evoke coordinated forelimb movements in the awake primate$^{[85, 20]}$. It has been reported that each stimulation site produced a stereotyped posture in which the arm moved to the same final position regardless of its posture at the initial stimulation. In the most complex example, the monkey formed a frozen pose with the hand in a grasping position in front of the open mouth. The reported experimental result implies that
Figure 3.2: The new coordinate system composed of \( P_w, P_e, P_s \) and \( P_m \): a) Each element \( J_i \) in the Jacobian matrix is defined with respect to the newly defined frame on the shoulder where the \( x \) axis is defined as \( (P_w - P_s)/\|P_w - P_s\| \) and \( y \) axis sits on the plane \( S \) composed of \( P_w, P_e \) and \( P_s \). The new frame on the shoulder is defined for the convenience of the calculation. b) Manipulability ellipsoid on the wrist position. \( u_1, u_2 \) and \( u_3 \) indicate the three major axis of the ellipsoid with magnitude of \( \sigma_1, \sigma_2 \) and \( \sigma_3 \).

during the arm movement toward an actual target, the virtual target point on the head can be set for the potential retraction point of the palm to the virtual target[Fig.3.1(b)].

3.1.1 Manipulability Ellipsoid and the Arm Redundancy Resolution criteria

The principle concept that is stated as apart of the hypothesis is associated with manipulability ellipsoid. For the combined arm joint velocities satisfying the condition stated as \( \Sigma_{i=1}^{n} \dot{\theta}_i^2 = 1 \), the hand velocity as a function of the arm joint velocity is described by an ellipsoid also known as the manipulability ellipsoid. The orientation of the ellipsoid with its three major axes is defined by the eigenvectors of the jacobian and the lengths of the major axes are defined.
Figure 3.3: The new coordinate system composed of $P_w$, $P_e$, $P_s$ and $P_m$: a) The highest manipulability direction vector $u_1$ projected on the $(P_m - P_w)/\|P_m - P_w\|$ is marked as the green arrow and its magnitude can be represented as $\|u_1\|\cos(\alpha)\cos(\beta)$. b) This figure shows the specific elbow position for the given wrist position that maximizes the manipulability projected on the virtual trajectory. When $P_m$, $P_s$, $P_e$ and $P_w$ are on the same plane, the manipulability on the virtual trajectory is maximized.

by the eigenvalues of the Jacobian. The largest among the major axes of the manipulability ellipsoid defines the direction in which the hand is more likely to move[74] and the best mapping between the arm joint space and the end effector (hand) Cartesian space [Fig.3.2(b)]. Point $P_m$ is defined as the attraction point for the head and point $P_w$ defines the location of the wrist joint position. A straight virtual trajectory is then defined passing through points $P_m$ and $P_w$ (Fig.3.1(b)). Then the proposed criteria for the arm redundancy resolution is that the selected swivel angle for the natural arm posture is chosen in a way the projection of the longest axis of the manipulability ellipsoid onto the virtual trajectory $(P_m - P_w)$ is maximized. By doing this, the proposed hypothesis in the previous section can be mathematically formulated as follows.
3.1.1.1 Manipulability Ellipsoid on the Wrist

Let the plane $S$ defined by three points $P_w$, $P_e$ and $P_s$. The longest axis of the manipulability ellipsoid is aligned along a plane $S$ and the magnitude of the longest axis $\sigma_1$ is defined as

$$\sigma_1 = \sqrt{\frac{\left((L_{ws}^2 + L_{we}^2) + (L_{ws}^2 + L_{we}^2)c_1\right)}{2}}$$

$$c_1 = \sqrt{1 - c_2}, \quad c_2 = 4L_{ws}^2L_{we}^2\sin^2(\phi) / (L_{ws}^2 + L_{we}^2)^2$$

where $L_{ws} = \|P_w - P_s\|$ and $L_{we} = \|P_w - P_e\|$. This result is based on the following derivation.

A new coordinate frame is defined with an origin at $P_s$ [Fig.3.2(a)] for the computational purpose. In this frame, the $z$ axis is orthogonal to the plane $S$ and the $x$ axis is aligned with the vector $(P_w - P_s)$. Then the relationship between the end effector velocity $\dot{P} = [\dot{x}_w \dot{y}_w \dot{z}_w]^T$ and the joint velocity $\dot{\theta}_{1234} = [\dot{\theta}_1 \dot{\theta}_2 \dot{\theta}_3 \dot{\theta}_4]^T$ is defined as follows

$$\dot{P} = J\dot{\theta}_{1234} = [J_1 J_2 J_3 J_4] \dot{\theta}_{1234}$$  \hspace{1cm} (3.1)

$$= [J_1 \dot{\theta}_1 + J_2 \dot{\theta}_2 + J_3 \dot{\theta}_3 + J_4 \dot{\theta}_4]$$  \hspace{1cm} (3.2)

$$J_i = \begin{cases} 
\omega'_i \times (P_w - P_s), & i = 1, 2, 3 \\
\omega'_i \times (P_w - P_e), & i = 4 
\end{cases}$$  \hspace{1cm} (3.3)

where $\omega'_i$ denotes the rotation axis of the $i$th joint. By introducing a new variable $\phi$[Fig.3.2(a)]
to represent $\mathbf{J}_4$ and using the fact that $\mathbf{\omega}'_1 = \mathbf{\vec{x}}$, $\mathbf{\omega}'_2 = \mathbf{\vec{y}}$ and $\mathbf{\omega}'_3 = \mathbf{\vec{z}}$ in Fig.3.2(a), we have

\[
\begin{align*}
\mathbf{J}_1 &= \mathbf{\vec{x}} \times (P_w - P_s) = 0 \quad (3.4) \\
\mathbf{J}_2 &= \|P_w - P_s\|[0 \ 0 \ -1]^T \quad (3.5) \\
\mathbf{J}_3 &= \|P_w - P_s\|[0 \ 1 \ 0]^T \quad (3.6) \\
\mathbf{J}_4 &= \|P_w - P_e\|[-\sin(\phi) \ \cos(\phi) \ 0]^T \quad (3.7)
\end{align*}
\]

Plugging Eq. 3.4, Eq. 3.5, Eq. 3.6 and 3.7 into Eq. 3.2 results in

\[
\dot{\mathbf{P}} = \mathbf{J}_2 \dot{\theta}_2 + \mathbf{J}_3 \dot{\theta}_3 + \mathbf{J}_4 \dot{\theta}_4 = [\mathbf{J}_2 \ \mathbf{J}_3 \ \mathbf{J}_4] \dot{\theta}_{234} \quad (3.8)
\]

\[
= \begin{pmatrix}
0 & 0 & -L_{w_e} \sin(\phi) \\
0 & L_{w_s} & L_{w_e} \cos(\phi) \\
-L_{w_s} & 0 & 0
\end{pmatrix}
\dot{\theta}_{234} = \mathbf{J}_{234} \dot{\theta}_{234} \quad (3.9)
\]

where $L_{w_s} = \|P_w - P_s\|$ and $L_{w_e} = \|P_w - P_e\|$. According to the singular value decomposition, $\mathbf{J}_{234}$ can be represented as $\mathbf{J}_{234} = \mathbf{UDV}^T$ where $\mathbf{U} = [u_1 \ u_2 \ u_3]$, $\mathbf{V} = [v_1 \ v_2 \ v_3]$ and $\mathbf{D} = \text{diag}[\sigma_1 \ \sigma_2 \ \sigma_3]$. The $u_i$ in the left singular vector $\mathbf{U}$ indicates one of the three axis constructing the manipulability ellipsoid and singular value $\sigma_i$ in $\mathbf{D}$ indicates the magnitude of the $u_i$ as shown in Fig.3.2(b). Note that $u_i$ and $\sigma_i$ are the eigenvectors and square root of the non-zero eigenvalues of $\mathbf{J}_{234}^* \mathbf{J}_{234}^*$.

\[
\mathbf{J}_{234}^* \mathbf{J}_{234} = \begin{pmatrix}
L_{w_e}^2 \sin \phi^2 & -L_{w_e}^2 \sin \phi \cos \phi & 0 \\
-L_{w_e}^2 \sin \phi \cos \phi & L_{w_s}^2 + L_{w_e}^2 \sin \phi^2 & 0 \\
0 & 0 & L_{w_s}^2
\end{pmatrix} \quad (3.10)
\]

Solving $\det(\mathbf{J}_{234}^* \mathbf{J}_{234} - \lambda \mathbf{I}) = 0$ allows to obtain $u_i$ and $\sigma_i = (\sqrt{\lambda_i})$. Based on Sarrus’s rule[68]...
the following expressions for the Eigenvalues are obtained.

\[ \lambda_{1,2} = \frac{(L_{ws}^2 + L_{we}^2) \pm (L_{ws}^2 + L_{we}^2) c_1}{2}, \quad (\lambda_1 > \lambda_2) \]

\[ c_1 = \sqrt{1 - c_2}, \quad c_2 = \frac{4L_{we}^2 L_{ws}^2 \sin(\varphi)^2}{(L_{ws}^2 + L_{we}^2)^2} \]

\[ \lambda_3 = \frac{L_{ws}^2}{2} \] \quad (3.11)

One may note that \( 0 \leq c_2 \leq 1 \) and \( 0 \leq c_1 \leq 1 \) such that \( \lambda_{1,2} \) are not complex numbers. The relationships between \( \lambda_1, \lambda_2 \) and \( \lambda_3 \), is studied by using two individual cases.

case1: \( (L_{ws} \geq L_{we}) \)

\[ \lambda_1 - \lambda_3 = \frac{(L_{ws}^2 - L_{we}^2) + (L_{ws}^2 + L_{we}^2) c_{min}}{2} \]

\[ \geq \frac{(L_{ws}^2 - L_{we}^2) + (L_{ws}^2 + L_{we}^2) c_{min}}{2} \]

\[ = \frac{(L_{ws}^2 - L_{we}^2) + (L_{ws}^2 + L_{we}^2) \sqrt{1 - c_{max}}}{} \]

\[ = \frac{(L_{ws}^2 - L_{we}^2) + (L_{ws}^2 + L_{we}^2) \sqrt{1 - \frac{4L_{we}^2 L_{ws}^2}{(L_{ws}^2 + L_{we}^2)^2}}}{2} \]

\[ = \frac{(L_{ws}^2 - L_{we}^2) + \sqrt{(L_{ws}^2 - L_{we}^2)^2}}{2} = 0 \] \quad (3.12)

where \( c_{min} \) and \( c_{max} \) are the minimum and maximum value of \( c_1 \) and \( c_2 \) respectively. The term \( c_{max} \) in Eq. 3.12 is defined as

\[ c_{max} = \max \frac{4L_{we}^2 L_{ws}^2 \sin(\varphi)^2}{(L_{ws}^2 + L_{we}^2)^2} = \frac{4L_{we}^2 L_{ws}^2}{(L_{ws}^2 + L_{we}^2)^2} \]
case 2: 

\[ L_{ws} < L_{we} \]

\[
\lambda_1 - \lambda_3 = \frac{(L_{ws}^2 + L_{we}^2) + (L_{ws}^2 + L_{we}^2) c_1}{2} - L_{ws}^2 \\
= \frac{(1 + c_1) (L_{ws}^2 + L_{we}^2)}{2} - L_{ws}^2 \\
\geq \frac{(1 + c_{min}) (L_{ws}^2 + L_{we}^2)}{2} - L_{ws}^2 \\
= \frac{(L_{we}^2 - L_{ws}^2)}{2} \geq 0 \quad (3.13)
\]

where the inequality in Eq. 3.13 is based on the fact that \( c_{min} = \min[c_1] = 0 \). The last line of inequality is valid since \( L_{ws} < L_{we} \). Therefore one may conclude that \( \lambda_1 \geq \lambda_3 \) in all range of \( L_{ws} \). It implies that the magnitude of the longest axis in the manipulability ellipsoid is

\[
\sigma_1 = \sqrt{\lambda_1} = \sqrt{\frac{(L_{ws}^2 + L_{we}^2) + (L_{ws}^2 + L_{we}^2) c_1}{2}} \quad (3.14)
\]

Based on the fact that the direction of the major axis of the manipulability ellipsoid corresponds to the eigenvector of the following Eq. 3.15, the eigenvector \( u_1 \) is obtained by applying the corresponding eigenvalue \( \lambda_1 \) to \( \lambda \) in Eq. 3.15.

\[
(J_{234} \cdot J_{234}^\ast) X = \lambda X, \quad X = [x \ y \ z]^T \quad (3.15)
\]

Then the direction of the eigenvector \( X \) in Eq. 3.15 is defined as

\[
y = \frac{\lambda_1 + L_{we}^2 \sin(\varphi) \cos(\varphi)}{-L_{we}^2 \sin(\varphi)^2} x = \left( \frac{-\lambda_1}{L_{we}^2 \sin(\varphi)^2} - \frac{1}{\tan(\varphi)} \right) x, \ z = 0 \quad (3.16)
\]

Considering the joint limit of the exoskeleton robot[97], it is assumed that \( 0 < \varphi \leq \pi/2 \). Note that when \( \varphi = 0 \), the arm is in a singular position. Then based on the fact that \( \lambda_1 > 0 \), the slope in Eq. 3.16 becomes negative. Fig. 3.3(a) depicts the direction of \( u_1 \) on plane \( S \).
3.1.2 Optimum Swivel angle

Reminding the fact that the longest axis of the manipulability ellipsoid defines the direction along which the hand is more likely to move than any other direction under the constraint \( \sum_i \theta_i^2 = 1 \), the optimum swivel angle is therefore defined such that the projection of the longest axis \( u_1 \) on the vector \((P_m - P_w)\) is maximized for the given wrist position as in Eq. 3.17.

Note that the vector \((P_m - P_w)\) is the direction of the shortest path between the end effector and the attraction point at the head.

\[
\phi = \arg\max_{\alpha, \beta \in [0 \pi/2]} \|u_1\| \|P_m - P_w\| \cos(\alpha) \cos(\beta)
\]

where \(\alpha\) and \(\beta\) indicate the angle between \((P_m - P_w)\) and plane \(S\), and the angle between \(u_1\) and the projection of \((P_m - P_w)\) onto \(S\) equivalently \((P_x - P_w)\)[Fig. 3.3(a)]. Note that the projected portion of \(u_1\) onto \((P_m - P_w)/\|P_m - P_w\|\) is represented as \(\|u_1\| \cos(\alpha) \cos(\beta)\) marked as a vector by a green arrow in Fig. 3.3(a). By introducing \(\gamma\) which is an angle between \((P_s - P_w)\) and \((P_x - P_w)\) from Fig. 3.3(a), we know

\[
\cos(\beta) = \cos(\pi/2 - \gamma - \psi) = \sin(\gamma + \psi)
\]

\[
= c_3 \sin(\gamma) + c_4 \cos(\gamma)
\]

\[
= \frac{c_3 \|P_s - P_c\| + c_4 \|P_c - P_w\|}{\|P_s - P_w\|}
\]

\[
= \frac{c_3 \|\vec{f} \cdot \frac{P_c - P_s}{\|P_c - P_s\|}\| + c_4 \|P_c - P_w\|}{\|P_s - P_w\|}
\]

\[
= \frac{c_3 \|\vec{f} \| \cos(\eta) + c_4 \|P_c - P_w\|}{\|P_s - P_w\|}
\]
where \( c_3 \) and \( c_4 \) mean \( \cos(\psi) \) and \( \sin(\psi) \) individually. Note that Eq. 3.19 is based on the fact that \((\gamma + \psi) \leq \pi/2\) and \( P'_c \) in Eq. 3.21 is the projection of \((P_m - P_w)\) onto \( n \) as shown in Fig. 3.3(a), \( \eta \) in Eq. 3.23 is the angle between \( \vec{f}' \), which is \( \vec{f} - (\vec{f} \cdot \vec{n}) \vec{n} \) in Fig. 3.3(a), and \((P_c - P_x)\). Based on the fact that \( \cos(\alpha) = \frac{||P_x - P_w||}{||P_m - P_w||} \), \( \cos \alpha \cos \beta \) in Eq. 3.18 can be written as

\[
\cos(\alpha) \cos(\beta) = \frac{||P_x - P_w||}{||P_m - P_w||} \frac{c_3 ||\vec{f}'|| \cos(\eta) + c_4 ||P'_c - P_w||}{||P_x - P_w||}
= \frac{c_3 ||\vec{f}'|| \cos(\eta) + c_4 ||P'_c - P_w||}{||P_m - P_w||}
= c_5 \cos(\eta) + c_6
\]

(3.24)

where constants \( c_5 \) and \( c_6 \) are \( c_3 ||\vec{f}'||/||P_m - P_w|| \) and \( c_4 ||P'_c - P_w||/||P_m - P_w|| \).

Then plugging Eq. 3.24 into Eq. 3.18 results in

\[
\phi = \arg \max_{\alpha, \beta \in [0, \pi/2]} [||u_1|| ||P_m - P_w|| (c_3 \cos(\eta) + c_4)]
\]

(3.25)

When \( \eta = 0 \), Eq. 3.25 is maximized and consequently \( \alpha \) in Eq. 3.24 becomes zero. Under this condition, plane \( S \) is coplanar with the plane defined by \( P_m, P_s \) and \( P_w \) as shown in Fig. 3.3(b). Therefore the swivel angle satisfying Eq. 3.25 for the Given \( P_m, P_w \) and \( P_s \) is computed as follows:

\[
\vec{f} = P_w - P_m
\]

(3.26)

\[
\vec{f}' = \vec{f} - (\vec{f} \cdot \vec{n}) \vec{n}
\]

(3.27)

\[
\phi = \arctan 2 \left( \vec{n} \cdot \left( \vec{f}' \times \vec{u} \right), \vec{f}' \cdot \vec{u} \right)
\]

(3.28)

Once the swivel angle estimation is completed, the actual joint angles \( \{\theta_1, \theta_2, \theta_3, \theta_4\} \) can be
computed by solving the following equations[82].

\[ T_1 T_2 \begin{bmatrix} P_{e_0} \\ 1 \end{bmatrix} = \begin{bmatrix} P_e(\phi) \\ 1 \end{bmatrix} \]  

(3.29)

\[ T_1 T_2 T_3 T_4 \begin{bmatrix} P_{w_0} \\ 1 \end{bmatrix} = \begin{bmatrix} P_w \end{bmatrix} \]  

(3.30)

where \( P_e(\phi) \) is the elbow position computed by combining Eq. 2.5 and Eq. 3.28. Note that \( P_{w_0} \) and \( P_{e_0} \) in Eq. 3.30 represent the initial position of the wrist and the elbow joint based on the exponential coordinates approach.

Then by substituting the computed joint angles based on Eq. 3.30 and Eq. 3.30 to \( \theta_c(t) \) in Eq. 2.11, desired joint angles to control exoskeleton robot are defined based on Eq. 2.10. Based on Eq. 3.28, it can be shown that a singularity occurs when \( \vec{f}' \) and \( \vec{u} \) are aligned.

### 3.2 Experimental Methodology

#### 3.2.1 Subject Definition

Ten right handed healthy subjects participated in the experiment to verify the proposed swivel angle estimation algorithm as a human arm motor control. Out of the ten subjects, eight were males and two were females. Their average age was thirty two years. In this experiment, subject’s joint angle data was collected while they were performing the given task sets and based on the collected experimental data, the computed swivel angels (\( \phi_{act} \)) were directly compared with the estimated swivel angle according to the proposed algorithm in Eq. 3.28.
Figure 3.4: Motion capturing marker locations and key point of interests: a) Positions of LED markers- Shoulder (Acromioclavicular joint), Elbow (Lateral edge of the Ulna), Wrist (Medial & Lateral edge of the distal end of the radius & ulna), Palm (between 2 & 3 metacarples) and Torso (Upper & lower sternum), b) Picture of the actual marker positions and c) $P_{ch}$ is the origin of the frame $F_{ch}$ and $P_o$ is the offset between $P_{ch}$ and $P_m$. Homogeneous transform matrix $T_{sh}^{ch}$ is defined between frame $F_{sh}$ and $F_{ch}$.

Figure 3.5: Experimental Setups: a) Target locations and dimensions of the experimental set up: Height of table-top to top-of-shelf=501.65mm, Height of table-top from ground=736.6mm and b) Three types of reaching task. In condition 'A' and 'B' of Type one, torso is facing 'b' and 'a' of the task space respectively while the condition 'C' is with the torso turned 45 degree counterclockwise off the Sagittal alignment and abducted hand points 'c'.
3.2.2 Experimental Tasks

Table 3.1: Tasks given in the experiment

<table>
<thead>
<tr>
<th>Type</th>
<th>Body Posture</th>
<th>Sequence</th>
<th>Number of Repetition</th>
<th>Object</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A,B,C</td>
<td>( o \rightarrow a \rightarrow b \rightarrow c \rightarrow d \rightarrow e \rightarrow f \rightarrow g \rightarrow h )</td>
<td>5</td>
<td>None</td>
</tr>
<tr>
<td>2</td>
<td>A:LR</td>
<td>( x \rightarrow l \rightarrow m \rightarrow x \rightarrow m \rightarrow l \rightarrow x \rightarrow x \rightarrow n \rightarrow b \rightarrow x \rightarrow b \rightarrow n \rightarrow x )</td>
<td>3</td>
<td>Ping pong ball/ Water bottle</td>
</tr>
<tr>
<td></td>
<td>A:BF</td>
<td>( x \rightarrow \text{Opencabinet} \rightarrow \text{Closecabinet} \rightarrow x )</td>
<td>3</td>
<td>Cabinet door</td>
</tr>
</tbody>
</table>

The three types of experimental protocols were derived from activities of daily living which included 1) arm reaching and pointing, 2) object manipulations both from a reference point to predefined locations in space in an unconstrained environment as well as 3) arm reaching and grasping while following a constrained trajectory. Table 3.1 summarize the the three
experimental setups defined for the current experiment plan, where the detailed description of
the experiment protocol will be describe in the following section. Fig. 3.5(b) depicts the dimen-
sion of the experimental setups and the configuration of the subjects body posture. Fig. 3.6 also
shows the actual image of the experimental setups.

3.2.2.1 Body Postures

Each subject was tested in a sitting posture with his/her torso restrained from torsional
movements. The distance between the subject and the table was adjusted based on the length
of the subject’s arm in order to avoid a full stretch of the arm (singular configuration). For the
type one protocol in the left box of Fig.3.5(b), each subject was positioned with respect to the
table in three different body postures. In body posture A, the subject faced the table and his/her
body was position such that the table and the subject’s body center lines were aligned. In body
posture B, the subject face the table as previously but center line was shifted to the left such that
it was aligned with the edge of the table. In body posture C, the body of the subject alignment
was the same as in (B) but the torso was rotated by 45 deg counterclockwise. For the rest two
types of protocols, the body is in posture A.

3.2.2.2 Targets and Objects

In the type one protocol, the subject use his/her index finger to point to the designated
targets. In the type two protocol, the subjects grasped a ping-pong (PP) ball and a water bottle
(WB) with the orientation of the wrist determined by themselves. The two objects were se-
lected to see the effect of the wrist orientation on the swivel angle during object manipulations.
Given the ping-pong ball geometry it has a negligible effect on the wrist orientation as opposed to the water bottle which dictates a specific final orientation and possibly affect the wrist orientation. The subjects repeat the experiments for the two different directions (LR: Left and Right) and (BF:Back and Forth) which resulted in four different tasks (LR:PP, LR:WB, BF:PP and BF:WB). In the type three protocol, the subject grasped a handle of a cabinet door. This protocol strictly determines the wrist orientation unlike the type two protocol.

3.2.2.3 Sequence

Each subject was instructed to position the hand in an initial location (‘o’ or ‘x’) and then move the hand in a self paced fashion between predefined locations as defined in Fig. 3.5(b). The target movement sequence which subjects should follow are defined in Table. 3.1.

3.2.2.4 Number of repetitions

The subject was instructed to repeat the task three or five times as defined for each specific task in Table. 3.1

3.2.3 Data Collection

The kinematic data of the human arm is collected using the Phasespace motion capture system (Phasespace, Inc.) including eight cameras with sub-millimeter accuracy. Active LED makers were attached to a subject’s body at key anatomical locations including shoulder($P_s$), elbow($P_e$), wrist($P_w$) and chest($P_{ch}$)[Fig. 3.4(a)]. The markers’ locations were sampled at 240
Hz for each channel of camera.

### 3.2.4 Data Post Processing - Optimum $P_m$ Estimation

![Exemplary plot of $P_m(t)$ for Type 1 and Type 2 from one subject: Upper row and lower row indicate the front and side view of (looking at the right shoulder) $P_m$ with respect to the shoulder (reference frame) in millimeter scale. In this figure, the black empty circles are indicating the right arm shoulder position $P_{sh}$. $P_m$ is individually estimated for each experiment and marked as a different color depending on the type of the tasks.](image)

Given the anthropometric differences between the subjects, the optimal target location $P_m$ for each subject was individually calculated. In order for his, we assume that the human body...
is considered to be symmetric and movement of the torso can be ignored. Thus the LED marker $P_{ch}$ on the chest [Fig. 3.4] as well as $P_m$ are located on the Sagittal plane [Fig. 3.4(c)], which equally divides the human body into left and right sections. If we define a reference frame $F_{ch}$ at $P_{ch}$[Fig. 3.4(c)], then the $P_m$ is represented by a fixed vector (time invariant) $P_o$ expressed with respect to the frame $F_{ch}$ (on the Sagittal plane) as follows:

$$
\begin{bmatrix}
P_{m}(t) \\
1
\end{bmatrix} =
\begin{bmatrix}
P_{ch}(t) \\
1
\end{bmatrix} + T_{sh}^{ch}(t) \begin{bmatrix}
P_o \\
1
\end{bmatrix}
$$

(3.31)

where $P_o$ is a vector representing a constant time invariant translation offset from $P_{ch}$ expressed in frame $F_{ch}$ and $T_{sh}^{ch}$ is the homogeneous transform matrix between the frame attached to the shoulder and one attached to the chest as depicted in Fig. 3.4(c). Then according to Eq. 3.26, the optimum offset $P_o$ is chosen to minimize the difference between $\phi(t)_{est}$, estimated swivel angle based on Eq. 3.26 and $\phi(t)_{act}$, calculated swivel angle given the measured joint angles.

$$
\arg\min_{y,z \in U_s} \int \int_{y,z} \left( \int_{x_{opt}}^{x_{opt}+T} |\phi(t)_{act} - \phi(t,P_o(y,z))_{est}| dt \right) dzdy
$$

(3.32)

where $U_s$ represents $(y,z)$ coordinate pairs on the Sagittal plane [Fig. 3.4(c)]. Since it is assumed that $P_m$ is located on the Sagittal plane, $x_{opt}$ is same as the x coordinate of $P_{ch}(t)$. Note that only a subset of the data were used to calculate the optimal location of $P_m$, as a result, $T$ in Eq. 3.32 corresponds to 1/5 of total data recording time. The estimated location of $(y,z)$ pair defining $P_o$ is summarized in the last column of Table. 3.4.

In addition Fig. 3.7 shows the realtime trajectory of the $P_m$ with respect to the right arm shoulder position. One may find out that the trajectory is around the actual head region.
However note that due to the limited accuracy of the motion captures system, position of the marker on each joint and the lack of scapular movement in the human arm model, the estimated $P_m$ for each experimental task can not be perfectly same.

Table 3.2: Averaged absolute differences between measured and estimated Swivel angles for Type One

<table>
<thead>
<tr>
<th>Subject</th>
<th>Protocol Type one</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.34°±1.52</td>
<td>2.72°±1.85</td>
<td>3.77°±3.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3.22°±2.34</td>
<td>3.99°±2.58</td>
<td>2.08°±1.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>5.40°±2.59</td>
<td>6.25°±3.00</td>
<td>7.13°±3.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>5.12°±2.59</td>
<td>3.84°±2.20</td>
<td>3.05°±1.73</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>8.07°±4.32</td>
<td>4.63°±2.84</td>
<td>3.42°±2.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>6.08°±4.22</td>
<td>4.68°±3.49</td>
<td>4.82°±3.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>4.32°±2.62</td>
<td>4.94°±2.07</td>
<td>2.98°±1.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>3.82°±2.82</td>
<td>3.64°±2.56</td>
<td>3.77°±3.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2.19°±1.64</td>
<td>4.96°±2.22</td>
<td>3.65°±2.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>3.85°±2.74</td>
<td>4.69°±3.23</td>
<td>5.98°±3.50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.3: Averaged absolute differences between measured and estimation swivel angles for Type Two

<table>
<thead>
<tr>
<th>Subject</th>
<th>Protocol Type two</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.66°±4.15</td>
<td>4.10°±3.05</td>
<td>5.04°±3.02</td>
<td>4.96°±3.70</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>4.82°±2.24</td>
<td>5.79°±2.98</td>
<td>7.13°±3.61</td>
<td>6.11°±3.94</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>4.80°±2.87</td>
<td>3.45°±2.64</td>
<td>4.07°±2.79</td>
<td>4.93°±3.12</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>9.04°±5.51</td>
<td>5.16°±4.27</td>
<td>5.30°±2.75</td>
<td>6.80°±3.60</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>7.91°±3.31</td>
<td>8.50°±4.52</td>
<td>8.85°±6.18</td>
<td>5.73°±3.55</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>4.63°±4.14</td>
<td>3.93°±2.17</td>
<td>3.22°±2.04</td>
<td>4.22°±3.06</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>8.35°±5.17</td>
<td>7.18°±3.94</td>
<td>5.48°±2.72</td>
<td>5.88°±3.17</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>8.21°±5.55</td>
<td>5.29°±3.07</td>
<td>3.62°±2.11</td>
<td>5.54°±3.76</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>7.15°±3.64</td>
<td>4.52°±2.70</td>
<td>6.24°±3.89</td>
<td>6.35°±3.62</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>9.36°±4.55</td>
<td>5.07°±4.12</td>
<td>6.50°±3.56</td>
<td>8.17°±4.93</td>
<td></td>
</tr>
</tbody>
</table>
Table 3.4: Averaged absolute differences between measured and estimation swivel angles for Type three and $P_o$ vector for each subject

<table>
<thead>
<tr>
<th>Subject</th>
<th>Opening cabinet</th>
<th>$P_o(y,z)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.50°±3.00</td>
<td>(-160, 280)</td>
</tr>
<tr>
<td>2</td>
<td>4.03°±2.92</td>
<td>(-140, 320)</td>
</tr>
<tr>
<td>3</td>
<td>4.67°±2.69</td>
<td>(-160, 390)</td>
</tr>
<tr>
<td>4</td>
<td>4.09°±2.92</td>
<td>(-70, 290)</td>
</tr>
<tr>
<td>5</td>
<td>7.73°±5.12</td>
<td>(-160, 170)</td>
</tr>
<tr>
<td>6</td>
<td>4.84°±3.74</td>
<td>(-150, 300)</td>
</tr>
<tr>
<td>7</td>
<td>4.81°±3.06</td>
<td>(-80, 250)</td>
</tr>
<tr>
<td>8</td>
<td>5.64°±2.97</td>
<td>(140, 330)</td>
</tr>
<tr>
<td>9</td>
<td>6.20°±4.21</td>
<td>(-100, 310)</td>
</tr>
<tr>
<td>10</td>
<td>2.73°±2.17</td>
<td>(-60, 220)</td>
</tr>
</tbody>
</table>

3.3 Results

In this section, the accuracy of the estimated swivel angle will be quantitatively evaluated for the given experimental setups described in the previous section. For the performance estimation, the mean and standard variation of absolute difference $e(t) = |\phi(t)_{act} - \phi(t,P_o(x,z))_{est}|$ between the measured swivel angle collected from the subjects during the experiments and the estimated swivel angle based on the proposed criterion were calculated. The performance estimation results for all the tasks are summarized in Table 3.2, 3.3 and 3.4. In addition, the $e(t)$ as a function of time is plotted for the subset of all subjects during multiple repetitions in Fig.3.9. The periodic nature of these plots are due to the multiple repetitions of the same task. The swivel angle difference are in the range of 2.1-8.1 deg for type one protocol, 3.5-9.4 deg for type two protocol, and 2.7-6.2 for type three protocol. Averaging the difference of the swivel angle across the entire data base indicated that the estimated value is different by less than 5 deg from the measured value. Two ways ANOVA analysis of the data with a confidence level of 95% indicated experimental protocol Type two (LR:PP) showed statistically
significant difference from all the other tasks and there are no significant difference between the subjects.

There are several sources for error resulting from: (1) inherent measurement error generated by the motion capture system, (2) torso rotation that took place in spite of the physical constraints (3) imperfect sensor locations with respect to the anatomical bony structures and the associated flexibility of the skin. Specifically in Type two protocol, LR:PP or LR:WB tasks requires the hands to move from the right hand work space to the left hand work space which can create inevitable torso rotation, which is not included in our human arm kinematic model and might affect the high estimation error.
Figure 3.9: Comparison between estimated swivel angle (dotted line) and calculated swivel angle (solid line) from two different subjects for Type one task: Each row shows the comparison result for Type one(A), Type one(B) and Type one(C) from two subjects. Figure a), c) and e) are for the subject one while Figure b), d) and f) are results for the subject two.
Figure 3.10: Comparison between estimated swivel angle (dotted line) and calculated swivel angle (solid line) from two subjects for Type two task: Figure a), c), e) and g) show the comparison result for Type two(LR:PP), Type two(LR:WB), Type two(BF:PP) and Type two(BF:WB) from the subject one while Figure b), d), f) and h) are results from the subject two.
Figure 3.11: Comparison between estimated swivel angle (dotted line) and calculated swivel angle (solid line) from two subjects: Figure a) shows the comparison result for Type three from the subject one while Figure b) is result from the subject two under the same condition as subject one

3.4 Swivel Angle Estimation Based on a Dynamic Constraint

Although the estimated swivel angle based on the purely kinematic constraint in Section 3.1 provided good estimation result, it is clear that the dynamic aspect of the manipulator affects the joint configuration during the movement. Thus merging the dynamic effect of the human arm movement into the swivel angle estimation can provide an improved estimation result and reveal the contribution of dynamic effect to the redundancy of the human arm movement. In this context, the redundancy of the human arm movement can be resolved by optimizing a cost function at the dynamic level. For instance, the work in [55] proposed to solve the 3D inverse kinematics problem based on minimizing the magnitude of total work done by joint torques for each time step. This dynamic criteria had generated satisfactory prediction of the joint space trajectory for the fundamental motions of the human arm, such as the shoulder adduction/abduction, the shoulder flexion/extension, the shoulder internal/external and the elbow
flexion/extension. To close the gap between the measured and estimated swivel angle in the kinematic level, minimizing the magnitude of total work criteria will be adopted as a dynamic constraint in this paper. However note that other dynamic criteria can also be used to improve the estimation performance in the future.

3.4.1 Minimum Work as a Dynamic Constraint

<table>
<thead>
<tr>
<th>i − 1</th>
<th>i</th>
<th>α_i</th>
<th>a_i</th>
<th>d_i</th>
<th>\theta_i</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_1(t) − 32.94°</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_2(t) − \pi/2 − 28.54°</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_3(t) − \pi − 53.6°</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_4 + \pi/2</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_5 + \pi/2</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_6 + \pi/2</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>\pi/2</td>
<td>0</td>
<td>0</td>
<td>\theta_7 + \pi</td>
</tr>
</tbody>
</table>

Table 3.5: Denavit-Hartenberg (DH) parameters for the dynamic model for the right human arm (modified method).

In the same way as done in the previous section, we restrict the scope of research to the simple reaching and grasping motion to minimize the wrist orientation effect on the redundancy resolution. To analyze the reaching motion at dynamic level, the dynamic model of the right human arm is rendered via the Autolev package [29], which generates the motion equation by Kane’s method [54]. This dynamic model processes seven DOFs (three DOFs for the shoulder, three DOFs for the wrist and one DOF for the elbow motion), with the frame setup in accordance with the EXO-UL7. The Denavit-Hartenberg parameters (DH) for the dynamic model (Table 3.5) are derived via the modified method [14]. Since the analysis of reaching motion in free space focuses on the wrist position of the human arm, the orientation of the
human hand in the dynamic model is pre-specified by locking the three DOFs at the wrist joint.

The dynamic modelling of the right human arm requires dimension measurements of the upper arm and lower arm and the estimation of dynamic parameters including (1) the mass, (2) the center of mass and (3) the moments of inertia for the upper arm, lower arm and hand. For each subject, the length of each segment was averaged during each individual experiment for the precise estimation. The upper arm length is the averaged distance between the shoulder marker and elbow marker during. The lower arm length is the averaged distance between the elbow marker and the estimated wrist position (based on the three markers around the wrist). The center of mass for each arm segment is estimated based on [96]. Refer to Table 3.6 for their percentages with respect to segment length. The mass and moments of inertia for each segment are calculated based on the weight of subjects according to the regression equations in [78]. The principle axes of each arm segment are shown in Fig. 3.12. The regression equations for the mass and moment of inertia follow the formats of

\[
\text{SegmentWeight} = c_1 \cdot \text{BodyMass} + r_1 \quad (3.33)
\]

\[
I_{xx} = c_{xx} \cdot \text{BodyMass} + r_{xx} \quad (3.34)
\]

\[
I_{yy} = c_{yy} \cdot \text{BodyMass} + r_{yy} \quad (3.35)
\]

\[
I_{zz} = c_{zz} \cdot \text{BodyMass} + r_{zz} \quad (3.36)
\]
The principle axes of moment of inertia for right arm segments: (a) the upper arm, (b) the lower arm, and (c) the hand.

The unit of segment mass and body mass (denoted as $\text{BodyMass}$) is $gm$. The unit for moment of inertia is $gm \cdot cm^2$. Table 3.7 and Table 3.8 show the corresponding coefficients in the regression of mass and moment of inertia for each arm segment, respectively.

| Table 3.7: Coefficients in the regression of segment mass for each arm segment. |
|---------------------------------|-----|-----|-----|-----|
| Upper Arm                      | $c_1$ | $r_1$ | $c_1$ | $r_1$ |
| Lower Arm                      | 0.0160 | 809 | 0.02 | -218 |
| Hand                           | 0.007 | -30 |

| Table 3.8: Coefficients in the regression of moment of inertia for each arm segment. |
|---------------------------------|------|------|------|------|------|------|
| Segments                       | $c_{xx}$ | $r_{xx}$ | $c_{yy}$ | $r_{yy}$ | $c_{zz}$ | $r_{zz}$ |
| Upper Arm                      | 0.535 | 98105 | 0.661 | 89662 | 0.400 | -4018 |
| Lower Arm                      | 1.508 | -31431 | 1.397 | -26562 | 0.313 | -11645 |
| Hand                           | 0.129 | -850 | 0.134 | -2599 | 0.085 | -3401 |

For a reaching motion in 3-D space, the wrist position of a human arm can be uniquely defined by three variables in the task space, while in the joint space there are four joint angles (three for the shoulder motion and one for the elbow motion) available for configuration. Accordingly, the relationship between movement and muscle forces in a musculoskeletal model is
based on the four dynamic equations [55] as:

\[ T = M \ddot{Q} + C(Q, \dot{Q}) + G(Q) \]  

(3.37)

In Eq. 3.37, \( \ddot{Q} = [\ddot{q}_1, \ddot{q}_2, \ddot{q}_3, \ddot{q}_4] \) and \( \dot{Q} = [q_1, q_2, q_3, q_4] \), where \( q_i \) represents the joint angle for the \( i \)th DOF. \( M, C(Q, \dot{Q}) \) and \( G(Q) \) represents the moment of inertia, the centrifugal/coriolis forces and the gravity force respectively. The external force is regarded as zero in this paper since the given task does not involve interacting with an external load. The active and passive joint torque rendered by musculotendinous forces are represented by \( T \). The calculation of work in joint space for each time step depends on the joint torque and the difference in joint angles. Therefore, the work in joint space during the movement interval \([t_k, t_{k+1}]\) can be computed for two different conditions. Since the dynamic constraint adopted in this paper is from the original work done by [78], we briefly include the essential part for the integrity of the paper.

**Work in the joint space during the movement interval**

When \( T_{i,t_k} \cdot T_{i,t_{k+1}} > 0 \),

\[ W_i = \frac{(T_{i,t_k} + T_{i,t_{k+1}}) \cdot \Delta q_i}{2} \]

(3.38)

where \( T_{i,t_k} \) and \( T_{i,t_{k+1}} \) are the torque of the \( i \)th joint at time \( t_k \) and \( t_{k+1} \). \( \Delta q_i = (q_{i,t_{k+1}} - q_{i,t_k}) \) is the difference of the \( i \)th joint angle during the time interval \([t_k, t_{k+1}]\).

When \( T_{i,t_k} \cdot T_{i,t_{k+1}} < 0 \),

\[ W_i = \frac{(|\Delta q_i| - h_i) \cdot T_{i,t_{k+1}} - h_i \cdot T_{i,t_k}}{2} \]

(3.39)

where \( h_i = (|T_{i,t_k}| \cdot |\Delta q_i|) / |T_{i,t_{k+1}} - T_{i,t_k}| \) and it has the significance for the difference of the \( i \)th joint angle from \( q_{i,t_k} \) to the joint angles corresponding to zero crossing of joint torque.
To minimize the work done in joint space for each time step (e.g., \( |W|_{t_k, t_{k+1}} \) for the time interval \([t_k, t_{k+1}]\)), the swivel angle of the human arm for a specified wrist position trajectory is optimized by the following cost function:

\[
C_T = |W|_{t_k, t_{k+1}} = \sum_{i=1}^{4} |W_i|_{t_k, t_{k+1}}
\]

(3.40)

where \( |W_i|_{t_k, t_{k+1}} \) denotes the work done by \( i \)th joint.

### 3.4.2 Combined swivel angle estimation based on kinematic and dynamic criteria

In this section we explain how two different constraints are combined to define the swivel angle. The overall estimation mechanism follows the concept of well known linear dynamic equation to combine two different swivel angle estimation result based on the kinematic and dynamic constraints with different weighting coefficient as follows:

\[
\phi_{optimal} = K_1 \cdot \phi_{kin} + K_2 \cdot \phi_{dyn}
\]

(3.41)

where \( \phi_{kin} \) and \( \phi_{dyn} \) denote the swivel angles predicted by the kinematic and dynamic constraints respectively. \( K_1 \) and \( K_2 \) are the weighting coefficients that represent the contribution of each constraint on the swivel angle estimation. This form of combination scheme is advantageous in case we find out more effective criteria. By simply extending the linear dynamic equation in Eq. 3.41 to one in Eq. 3.42, more general form of swivel angle estimation is given by

\[
\phi_{optimal} = \sum_{i=1}^{N} K_i \cdot \phi_i
\]

(3.42)
where \( \phi_i \) and \( K_i \) mean the estimated swivel angle from the \( i \)th constraint and the corresponding weighting coefficient. However note that unlike the kinematic and dynamic criteria introduced so far, it is hard to combine the redundancy resolution of the constrained human arm movements such as an obstacle avoidance and playing sports with the other criteria for the unconstrained human arm movements based on the linear dynamic equation. The constrained human arm movement is highly dependent on the surrounding environment such that the reaction against the environment significantly varies among subjects. In order to accommodate the effect based on the constrained human arm movement into the redundancy resolution of the human arm, we consider the admittance control based on the force feedback as a background control scheme. The detailed description for this control strategy will be further introduced in the next section.

As we already mentioned in the previous section, the weighting coefficient \( K_1 \) and \( K_2 \) are estimated by using the joint angle data associated with a given arm movement task, which is collected by the motion capture system. According to the Type one experimental protocol, subjects repeat a given task. The first cycle of the data will be exploited to determine the optimum \((K_1, K_2)\) based on the least square solution. Let \( \phi_{act}(t) = K_1 \cdot \phi_{kin}(t) + K_2 \cdot \phi_{dyn}(t) + n(t) \) where \( n(t) \) is the measurement error or noise component of the system. Then if we define
column vectors $X$ and $Y$, and a matrix $A$ as:

$$Y = \begin{bmatrix}
\phi_{act}(t_0) \\
\phi_{act}(t_1) \\
\vdots \\
\phi_{act}(t_{N-1})
\end{bmatrix}, \quad A = \begin{bmatrix}
\phi_{kin}(t_0) & \phi_{dyn}(t_0) \\
\phi_{kin}(t_1) & \phi_{dyn}(t_1) \\
\vdots & \vdots \\
\phi_{kin}(t_{N-1}) & \phi_{dyn}(t_{N-1})
\end{bmatrix}$$

$$X = \begin{bmatrix}
K_1 \\
K_2
\end{bmatrix} \quad (3.43)$$

The least square solution for the weighting coefficient vector based on Eq.3.43 is given by:

$$X = (A^T A)^{-1} A^T Y \quad (3.44)$$

3.5 Results

In order to evaluate the proposed swivel angle estimation performance and to see the effect of dynamic constraint on the swivel angle estimation, we follow the same verification protocol introduced in Section 3.2.4. Total of ten subjects participated in the experiment and repeated the given tasks for five times. $\phi_{kin}$ and the optimum $P_i$ for each subject were computed based on Eq. 3.26 and Eq. 3.32 respectively.

$$\phi_{estbi} = K'_1 \cdot \phi_{kin} + K'_1 \cdot \phi_{dyn} \quad (3.45)$$

where $K'_1$ and $K'_1$ mean the estimated weighting factors applied to the rest four repetition cycle data. The estimated weighting coefficients for each subject are summarized in the right three
Figure 3.13: Comparison between the estimated and measured swivel angle for one subject: The first column shows the comparison result and the data between two vertical lines in the first column is enlarged in the second column. Exp1, Exp2 and Exp3 indicate the estimation results when the center of the chest faces the center of the targets, leftmost target and when the body is rotated by 45 degrees. (Solid line: Computed swivel angle, Dotted line: swivel angle based on kinematic constraint, Dash dot line: Swivel angle based on dynamic constraint, Circle mark: combination of two swivel angles based on Eq. 3.41.)
columns of Table 3.9 together with \( P_o \).

Table 3.9: Estimated weighting coefficient and offset \( P_o \) for each subject

<table>
<thead>
<tr>
<th>Subject</th>
<th>((K_1, K_2))</th>
<th>((P_o, (x_{opt}, z_{opt})))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>((0.98, 0.02))</td>
<td>((-160, 280))</td>
</tr>
<tr>
<td>2</td>
<td>((1.00, -0.12))</td>
<td>((-140, 320))</td>
</tr>
<tr>
<td>3</td>
<td>((1.03, -0.24))</td>
<td>((-70, 290))</td>
</tr>
<tr>
<td>4</td>
<td>((1.11, -0.14))</td>
<td>((-140, 330))</td>
</tr>
<tr>
<td>5</td>
<td>((0.96, 0.00))</td>
<td>((-60, 220))</td>
</tr>
<tr>
<td>6</td>
<td>((1.14, -0.18))</td>
<td>((-100, 270))</td>
</tr>
<tr>
<td>7</td>
<td>((1.05, -1.22))</td>
<td>((-160, 170))</td>
</tr>
<tr>
<td>8</td>
<td>((0.98, 0.05))</td>
<td>((-80, 250))</td>
</tr>
<tr>
<td>9</td>
<td>((0.99, -0.067))</td>
<td>((-100, 310))</td>
</tr>
</tbody>
</table>

The final form of swivel angle based on the proposed redundancy resolution criteria was estimated for the given wrist position data recorded during the experiment. Fig. 3.13 shows the direct comparison result between the estimated and measured swivel angle. The first column in Fig. 3.13 shows the computed(measured) swivel angle(solid line), swivel angle \( \phi_{kin} \) based on kinematic constraint(dotted line) in Eq. 3.26, swivel angle \( \phi_{dyn} \) based on dynamic constraint(Dash dot line) in Eq. 3.40 and the combination of two swivel angles(circle mark) based on Eq. 3.41. Data between two vertical lines in the first column is enlarged in the second column of Fig. 3.13. Exp1, Exp2 and Exp3 indicate the estimation results which correspond to Type A, B and C in Fig. 3.5(b).

For more quantitative evaluation of the estimation algorithm, the estimation errors for all experiments are computed based on Eq. 3.46 and the statistical information about the
Figure 3.14: ANOVA test result for the normalized weighting coefficient \( \frac{|K_1|}{|K_1| + |K_2|} \): Result shows that \( P > 0.05 \) and there is no significant difference for the ratio of kinematic and dynamic aspect among subjects.

estimation error is listed in Table. 3.10.

\[
\arg\min_{y,z \in U_y} \int_y \int_z \left( \int_{t_y}^{t_y+T} \phi(t)_{act} - \phi(t,P_o(y,z))_{est} \right) dz dy \tag{3.46}
\]

3.6 Discussion

So far it is shown that redundancy of the human arm can be represented as the linear combination of two different swivel angles. The estimation results in Fig. 3.13 and Table. 3.10 shows that the \( \phi_{dyn} \) itself does not provide the good estimation for the unconstrained human arm reaching movement. By linearly combining \( \phi_{dyn} \) together with \( \phi_{kin} \) based on Eq. 3.41, the estimation result was significantly improved. For more quantitative evaluation of the estimation algorithm, the mean and standard deviation of the absolute estimation error across all the subjects are computed and listed in Table. 3.10. The result shows that combining \( \phi_{dyn} \) and \( \phi_{kin} \) improved the estimation performance such that mean error for the entire data sets is less than
Table 3.10: Estimation error analysis

<table>
<thead>
<tr>
<th>Subject</th>
<th>Mean and standard deviation of absolute error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exp 1 (Type A)</td>
</tr>
<tr>
<td></td>
<td>(dyn, kin, comb)</td>
</tr>
<tr>
<td>1</td>
<td>(37.4°, 1.8°, 1.7°)</td>
</tr>
<tr>
<td>2</td>
<td>(33.4°, 2.2°, 1.8°)</td>
</tr>
<tr>
<td>3</td>
<td>(42.7°, 1.4°, 0.4°)</td>
</tr>
<tr>
<td>4</td>
<td>(31.7°, 3.3°, 2.8°)</td>
</tr>
<tr>
<td>5</td>
<td>(36.5°, 3.5°, 3.2°)</td>
</tr>
<tr>
<td>6</td>
<td>(33.5°, 3.7°, 5.2°)</td>
</tr>
<tr>
<td>7</td>
<td>(51.6°, 6.8°, 5.7°)</td>
</tr>
<tr>
<td>8</td>
<td>(37.5°, 6.5°, 5.2°)</td>
</tr>
<tr>
<td>9</td>
<td>(25.8°, 4.3°, 4.3°)</td>
</tr>
<tr>
<td>10</td>
<td>(31.8°, 6.0°, 2.9°)</td>
</tr>
</tbody>
</table>

five degrees in most cases with less than four degrees of standard deviation except the result from subject 6, 7 and 8 in Exp1 (Type A) experiment [Fig. 3.5(b)]. In case of Exp1 (Type A) experiment, the three target locations are on the left side of the sigittal plane such that subject’s moving right hand toward the targets on the left side can easily accompany the rotation of the torso. Since our seven DOF arm model does not include torso model, it is possible that the estimation performance decreases for the Exp1 (Type A) experiment.

In addition, the result summarized in Table 3.9 reveals the importance of each constraint for the reaching and grasping tasks. The one way anova test in Fig. 3.14 was applied to \(|K_1|/(|K_1| + |K_2|)\) and it shows that there is no significant difference for the normalized weighting coefficient among subjects. This result implies that the dynamic effect on the human arm movement is not dominant due to the strong effect based on the hidden motor control scheme introduced in Eq. 3.26. This might result from the fact that our experimental protocol does not require the high speed and acceleration of each joint in most time duration. When the
Figure 3.15: Joint velocity, acceleration and corresponding swivel angle: a) the summation of joint acceleration $\sum_{i=1}^{4} |\ddot{\theta}_i(t)|$, b) the summation of joint velocity $\sum_{i=1}^{4} |\dot{\theta}_i(t)|$ and c) corresponding swivel angle based on the dynamic constraint

speed and acceleration of each joint get close to zero, the basic dynamic equation Eq. 3.37 can be approximated as

$$ T = M \ddot{Q} + C(Q, \dot{Q}) \dot{Q} + G(Q) $$

$$ \approx G(Q) \quad (3.47) $$

Accordingly, the cost function[Eq. 3.40] to extract the swivel angle will be simplified as

$$ C_T = \sum_{i=1}^{4} |W_i|t_{k_{i-1}} - t_{k_i} = \sum_{i=1}^{4} \left( \frac{T_{i_{k_i}} + T_{i_{k_{i+1}}}}{2} \right) \cdot \Delta q_i $$

$$ \approx \sum_{i=1}^{4} G(Q(i)) \Delta q_i \quad (3.49) $$

where $T_{i_{k_i}} \approx T_{i_{k_{i+1}}}$ in low speed and acceleration condition. Assuming that $\Delta q_i$ for the moderate speed regime is almost constant in a short time duration, the cost function to optimize has
only gravitational term and the swivel angle minimizing this cost function will be zero in our coordinate system [Fig. 2.2(a)]. In this condition, the elbow will be placed at its lowest position. Fig. 3.15 shows the summation of each joint acceleration $\sum_{i=1}^{4} |\ddot{\theta}_i(t)|$, the summation of each joint velocity $\sum_{i=1}^{4} |\dot{\theta}_i(t)|$ and corresponding swivel angle based on the dynamic constraint. In the specified regime with two vertical lines, the joint velocity and acceleration is low compared to those in the other time duration such that the corresponding swivel angle (third row) estimated by the dynamic constraint is almost zero. Since human arm does not have a non-zero swivel angle even in a static posture, the effect from the dynamic criterion on the human arm motor control can not be dominant. Thus it is desired to set up different inverse kinematic strategy depending on the velocity profile of the joint angles and the existence of the load on the arm.

3.7 Conclusions

The proposed swivel angle estimation algorithm is established by linearly combining two different swivel angles generated by kinematic and dynamic constraints. The estimation algorithm successfully reproduces the natural human arm movement with less than five degrees of estimation error in most cases. The result also reveals that although the bimodal approaches combining kinematic and dynamic improved estimation performance, the effect of the kinematic constraint on the redundancy resolution of the human arm is still dominant for the simple reaching and grasping tasks that does not require the high joint velocity. It is possible that human arm movement defined in our experimental protocol is maintained slow enough to ignore the dynamic effect of the human arm and there exists a hidden motor control scheme for all
subjects based on the kinematic constraint. Since the closed form swivel angle estimation based on the kinematic constraint itself provides precise swivel angle estimation with relatively low computational complexity, it can be applied to the realtime exoskeleton robot controller. For instance, the algorithm can be applied to the force field generation for the rehabilitation robotic system (wearable exoskeleton robot, EXO-UL7). By providing robot with a reference swivel angle, the robot can create the assistive force field based on the end effector or wrist position of the robot. For future work, more data can be collected with varios velocity profile to study the velocity or acceleration effect on the inverse kinematic mechanism of the human arm.
Chapter 4

Redundancy resolution with admittance control

4.1 Admittance control

Recent research has focused on the transparency of the human-robot system so that the operator feels less reaction from the wearable robot [99][28]. In particular, this research effort intends to develop a control strategy for an upper limb exoskeleton with seven degree of freedom (DOFs), so that it renders natural arm postures. The proposed admittance control scheme in this research is modified to accommodate both constrained and unconstrained human arm movements into a unified controller by utilizing a swivel angle estimation algorithm based on the kinematic constraint introduced in Section 3.1. The force interaction between the wearable robot and the user is extracted via four force sensors located on the wearable robot, such that the exoskeleton can render flexible movements for sophisticated tasks. The modified
The overall scheme for the proposed admittance control is described in Fig. 4.1. Due to the redundancy in the seven DOF robotic system, not only the handle but also the elbow angle velocity should be considered in the control. The wrist position and orientation are calculated independently in task space using the four force sensors.
Let $\phi_{eq}$ represent the predicted swivel angle for the unconstrained and natural arm posture in general. Then the desired swivel angle $\phi_d$ is the combination of predicted swivel angle $\phi_{eq}$ and the deviation of swivel angle $\Delta\phi$ from the $\phi_{eq}$ based on the force sensor information. Once the wrist position $P_w$ and orientation $R_{dw}$ are defined, together with swivel angle $\phi_d$, they are put through the inverse kinematic function [83] to create the desired joint angles $\Theta_d = \{\theta_{1d}, \theta_{2d}, \ldots, \theta_{7d}\}$ in Fig. 4.1 and joint trajectories are followed using PID control. In doing so, the predicted swivel angle can immediately provide the natural arm movement as an equilibrium state without force feedback. Assuming that the most of the human arm movement consists of simple reaching-grabbing task and the more sophisticated movements are initiated by deviation from the equilibrium status, the proposed admittance control structure can overcome the limitation of the purely reactive admittance control with relatively high energy exchanges between human and robot.

4.3 Admittance Control With Motion Prediction

In this section, the detailed description for the proposed admittance control algorithm is explained. Although $\phi_{eq}$ is employed as a general symbol for the equilibrium status of the human arm movement based on the specific criteria, the swivel angle estimation based on Eq. 3.28 will be applied to $\phi_{eq}$ in this approach [62].

The proposed admittance control scheme is composed of three parts which are wrist position estimation, wrist orientation estimation and the $\Delta\phi$ estimation along the swivel axis.
Figure 4.2: Force interactions at the upper arm create motion that is tangent to a sphere that is centered at the shoulder: (a) The x component of an upper arm force creates motion in the x direction at the upper arm and wrist, (b) The y component of the force creates a motion in the y direction at the upper arm but the motion is rotated by $\alpha$ at the wrist. The z component is resisted by the mechanism and does not result in motion and (c) Target location for the admittance control algorithm test with respect to the exoskeleton robot position.

### 4.3.1 Wrist Position based on Force feedback

Since the motions of the device due to the interaction forces will be in the same direction as the force vector, it is straightforward to relate the forces at the tip ($\vec{f}_t$), handle ($\vec{f}_h$) and lower arm ($\vec{f}_l$) to the position change of the wrist. However the spherical joint of the shoulder constrains any point on the upper arm to the surface of a sphere. Thus a force applied on the upper arm is tangential to the shoulder sphere and the perpendicular force component to the sphere is resisted by the device. Let’s define a frame at the origin of the upper arm force sensor. This frame has x, y and z axis pointing to the user’s right, forward and up when the arm is at the side. The z component of the upper arm force is zero since it is perpendicular to the sphere of motion. The x component creates different motion at the wrist according to the elbow rotation angle. When the vectors tangential to the surface of the spheres at the wrist and upper
arm are separated by the angle $\alpha$ as shown in Fig. 4.2(a), the original upper force signal ($\vec{f}_u$) gets transformed as follows:

$$
\vec{f}_u = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ y \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ \cos(\alpha) y \\ \sin(\alpha) y \end{bmatrix}
$$

(4.1)

To work with the four sets of force signals in a common frame, they are transformed based on $\vec{f}' = R_1 R_2 \ldots R_n \vec{f}$, where $\vec{f}$ is the force measurement, $n$ is the link frame to which the sensor is attached, and $\vec{f}'$ is the force represented in the global frame. Since the force between the user and the exoskeleton device should be zero in an ideal case, the error in the force ($\vec{f}_e$) will be

$$
\vec{f}_e = \vec{f}_u' + \vec{f}_h' + \vec{f}_t' - \vec{0}
$$

(4.2)

where $\vec{0}$ means the reference force. Next, we transform the force signals into a task space position signal as follows:

$$
x = k_p \vec{f}_e + k_i \int \vec{f}_e - k_d \dot{x}
$$

(4.3)

The last term ($-k\ddot{x}$) is from Hook's Law [100] for an approximate derivative of the noisy force signal.

### 4.3.2 Wrist Orientation based on Force feedback

Changes in the wrist orientation are calculated based on torque at the wrist. The handle and tip force sensor will produce torques at the wrist. Since neither the wrist sensor nor the tip sensors are located at the wrist, the torque at the wrist ($\vec{\tau}_w$) due to the handle will be the addition of the handle torque ($\vec{\tau}_h$) with the cross product of the handle distance ($\vec{r}_h$) and the
handle force ($\vec{f}_h$). Similarly, the torque at the wrist due to the tip will be the tip torque ($\vec{\tau}_t$) plus the cross product of the tip distance ($\vec{r}_t$) with the tip force ($\vec{f}_t$). The total torque at the wrist will be the addition of the contributions of the handle and the tip. Next, we transform $\vec{\tau}_w$ from the sensor frame into the global frame.

$$\vec{\tau}_w = \left[ \vec{\tau}_h + (\vec{r}_h \times \vec{f}_h) \right] + \left[ \vec{\tau}_t + (\vec{r}_t \times \vec{f}_t) \right]$$

(4.4)

$$\vec{\tau}_w' = R_1 R_2 R_3 R_4 R_5 R_6 R_7 \vec{\tau}_w$$

(4.5)

The desired reference torque is zero, making the error signal $\vec{\tau}_e = \vec{\tau}_w' - \vec{0}$. Taking $\vec{\tau}_e$ to be the axis angle representation for the change in orientation, a rotation matrix ($R_e$) can be constructed to represent the desired change.

$$\theta_e = ||\vec{\tau}_e||$$

(4.6)

$$\vec{\omega}_e = \frac{\vec{\tau}_e}{\theta_e}$$

(4.7)

$$R_e = I + \vec{\omega}_e \sin(\theta_e) + \vec{\omega}_e^2 (1 - \cos(\theta_e))$$

(4.8)

where $\theta_e$ is the desired change in angle, $\vec{\omega}_e$ is the rotation axis, $I$ is the $3 \times 3$ identity matrix, and $\vec{\omega}_e$ is the antisymmetric matrix equivalent of the cross product. With this, the desired orientation ($R_d$) becomes

$$R_d = R_e R_{d-1}$$

(4.9)

where $R_{d-1}$ is the desired orientation from the previous time step. At initiation $R_{d-1}$ is set equal to the current orientation of link seven.
4.3.3 Swivel Angle based on Force feedback

Changes in the swivel angle are calculated based on the torque on the swivel axis. In our case, only the upper and lower arm forces contribute to the torque around the swivel axis. The upper and lower arm sensors are measured in different frames and must be put into a common global frame. Then the total torque on the shoulder ($\vec{\tau}_s$) is the addition of the contributions from the upper and lower arm.

$$\vec{\tau}_s = \left[ \vec{\tau}_u' + (\vec{r}_u \times \vec{f}_u') \right] + \left[ \vec{\tau}_l' + (\vec{r}_l \times \vec{f}_l') \right]$$  (4.10)

where $\vec{\tau}_u'$ and $\vec{f}_u'$ are the torque and force at the upper sensor. Then similarly $\vec{\tau}_l'$ and $\vec{f}_l'$ are the torque and force at the lower arm. Only the component of torque that acts on the swivel axis will cause a change in the swivel angle. Thus the component of $\vec{\tau}_s$ acting on $\vec{n}$ (Eq. 2.1) is $\vec{\tau}_n = \vec{\tau}_s \cdot \vec{n}$. The desired reference torque is zero so the error is equal to $\vec{\tau}_e = \vec{\tau}_n - 0$ and the desired swivel angle change is:

$$\Delta \phi = k_p \vec{\tau}_e + k_i \int \vec{\tau}_e - k_d \dot{\vec{\tau}}_e$$  (4.11)

where the term $(-k_d \dot{\vec{\tau}}_e)$ is similarly defined as Eq. 4.3.

4.4 Experiment and Performance Analysis

Five right-handed healthy subjects (three male and two female subjects with an average height of 175 cm and an average age of 29) participated in the experiment to evaluate the proposed admittance controller. The kinematic data of the human arm is collected using a motion capture system as shown in Fig. 3.4(a) and the same experimental protocol is applied.
to extract the $P_o$ for $\phi_{eq}$ estimation, which is different among subjects. Please refer to the Section 3.2 for more detailed description about the experimental protocol to collect kinematic data of the subject. Then all the parameters will be imported to the robotic system and $\phi_{eq}$ based on the newly defined kinematic constraint[Eq. 3.28] can be computed in realtime.

### 4.4.1 Performance of the Proposed Admittance Control

The proposed admittance controller will be compared with the purely reactive admittance control algorithm without using $\phi_{eq}$. The interaction power, interaction energy, and completion time was calculated for each peg-in-hole task performed wearing the exoskeleton. The experimental setup for this peg-in-hole task is described in Fig. 4.2(c). The interaction power was calculated by adding the translational and rotational portion of the power at each
attachment point according to Eq. 4.13.

\[
P_{\text{total}} = P_{\text{translate}} + P_{\text{rotate}} \quad (4.12)
\]

\[
= \sum_{i=1}^{4} [\vec{f}_i \cdot \vec{v}_i + \vec{\tau}_i \cdot \vec{\theta}_i] \quad (4.13)
\]

where \(\vec{f}_i, \vec{v}_i, \vec{\tau}_i\) and \(\vec{\theta}_i\) mean the force vector, linear velocity, torque vector and joint velocity at \(i\)th sensor location. The translational power was obtained by taking the dot product of the force sensor data and the velocity calculated using the forward kinematic map and joint position data. Similarly, the rotational power was obtained as the dot product of the torque, recorded from the force sensors, with the angular velocity calculated using the encoder data and the forward kinematic map. Interaction energy was found by taking the integral of the power. The completion time was recorded between when the brake pedal for the robot was first pressed and when the pedal was released. For the comparison of power exchange between conventional and modified admittance controller, \(P_{\text{total}}\) in Eq. 4.13 has been normalized with respect to time.

Note that the statistical analysis is not performed due to not enough number of subjects and will be remained as a future work.

### 4.4.2 Experiment Setup to Evaluate the Proposed Admittance Control

The exoskeleton’s height was adjusted for each individual subject in a seated position. The subject was secured in the device with the two straps, one at the upper arm and the other at the lower arm. In front of the subject was a table with three target plates which are T1, T2 and T3 from the subject’s right to left as shown in Fig. 4.2(c). There is a resting position(RP) and this position is used as a reference position to begin and finish the each repetition for the
given task [Fig. 4.2(c)]. The exact locations of the targets and the resting position were defined in Fig. 4.2(c) as a meter scale. Note that z points up and is measured from the floor. Then each subject was instructed to touch the targets in the following order.

\[ RP \rightarrow T_1 \rightarrow RP \rightarrow T_2 \rightarrow RP \rightarrow T_3 \rightarrow RP(20\text{times}) \quad (4.14) \]

4.5 Result and Conclusion

The average power profile for all subjects is shown in Fig. 4.3. The solid line indicates the result based on the conventional admittance control scheme without equilibrium swivel angle information while the dotted line means the result based on the modified admittance control scheme. The power peaks in Fig. 4.3 correspond to pushing the exoskeleton towards or pulling back from targets while valleys occur when the subjects approached the target with their velocities reduced. Thus the power and the velocity profile from RP to each target match the well known bell-shape profile\[2][55]. The approach and retraction for each target is clearly distinguishable in the plot test and it can be seen that the further the target location the greater the interaction power. This is because it takes more time for the subject to accelerate the robot as the target is positioned farther from the starting point. Also note that when the swivel angle estimation is combined with the admittance control, peaks and valleys of the power profile are lower than those without swivel angle estimation support.

The interaction energy averaged over all subjects showed a statistically significant difference (at the .05 confidence level) depending on if swivel support was used. The interaction...
energy for the given task was 42.07 J with swivel angle estimation support and 46.79 J without swivel estimation support. This represents an 11.22% increase in the positive energy interaction when swivel support is not used. It is important to note that the interaction energy is the energy exchange between the robot and user and contains no information about the total energy of either system to complete the task. There was no statistically significant difference in the completion time when swivel support was added.
Chapter 5

Redundancy of the human arm based on the orientation of the end effector.

5.1 Swivel angle based on wrist orientation

There are many tasks in the daily living that requires rotation of the wrist. For example, rotating the door knob and pouring the water to the cup requires the wrist orientation changes for the nearly fixed wrist position. In many cases, it is also observed that the elbow position is affected by the wrist orientation change due to the muscular coupling between arm joints. Since one of the important control scheme required for the exoskeleton robot is to make the wearer and the robot move in a synchronized way, supporting the wearer with this type of movement can play an important role in the wearable robot control. In addition, wrist joints are easy to manipulate due to their low friction and light weight property which enable wearer to easily manipulate the shoulder joints of the upper limb exoskeleton by changing the wrist
orientation. This type of control scheme is advantageous since it does not require the noisy force/torque sensor signal. However interpreting this kind of human arm movement based on the previous introduced manipulability concept approach might not be proper considering the fact that the hand does not have a link length enough to affect the manipulability compared to the other arm links. In addition, the mass effect of the palm on the human arm dynamic are negligible such that the dynamic level approach will not be helpful to understand the redundancy resolution based on the wrist orientation change.

In this section, we explore the relationship between the wrist orientation change and the redundancy of the human arm to establish new control model that can predict the desired joint configuration as a function of wrist orientation changes. By combining this control model with the previously introduced swivel angle estimation model based on the wrist position, more generalized human motor control model can be established. Behind this approach, it is assumed that

*The redundancy of the unconstrained human arm movement can be represented as the superposition of two independent components which are swivel angles based on the wrist position and orientation.*

### 5.1.1 Manipulability based on the seven DOF arm model

Previously we introduced manipulability concept to define the redundancy of the human arm, which is defined as the swivel angle. Before we go to the main discussion about the motor control model based on the wrist orientation, the manipulability of the seven DOF model will be discussed to see if the same analysis model can be applied to define the control model.
Similarly from Section 3.1.1.1, Fig. 5.1(a) shows the necessary frame definition and the jacobian matrices. Since the natural arm posture for the given wrist position is already studied in Section 3.1.1.1, $P_m$, $P_s$, $P_w$ and $P_e$ in this definition are all located on the same plane $S$. It is also assumed that the wrist orientation in its initial state makes the hand segment $(P_T - P_w)$ sits on the plane $S$ as shown in Fig. 5.1(a). Note that $P_T$ indicates the center of the palm. Then the linear velocity $P_T$ at $P_T$ is defined as

$$
\dot{P}_T = \mathbf{J}_1 \dot{\theta}_1 + \mathbf{J}_2 \dot{\theta}_2 + \mathbf{J}_3 \dot{\theta}_3 + \mathbf{J}_4 \dot{\theta}_4 + \mathbf{J}_5 \dot{\theta}_5 + \mathbf{J}_6 \dot{\theta}_6 + \mathbf{J}_7 \dot{\theta}_7
$$

(5.1)

$$
\dot{\theta}_i = \omega_i \times (P_T - P_s), i = 1,2,3
\dot{\theta}_4 = \omega_4 \times (P_T - P_e), i = 4
\dot{\theta}_i = \omega_i \times (P_T - P_w), i = 5,6,7
$$

(5.2)

where $\mathbf{J}_1$ and $\mathbf{J}_5$ are zero since they do not affect the linear velocity at $P_T$. Then by plugging
Eq. 5.3 into Eq. 5.2, we can achieve

\[ \dot{P}_T = J_2 \dot{\theta}_2 + J_3 \dot{\theta}_3 + J_4 \dot{\theta}_4 + J_6 \dot{\theta}_6 + J_7 \dot{\theta}_7 = [J_2 \ J_3 \ J_4 \ J_6 \ J_7] \dot{\theta}_{23467} \] (5.4)

\[ = \begin{pmatrix}
0 & 0 & -L_{Te} \sin(\phi) & -L_{Tw} \sin(\phi) & 0 \\
0 & L_{Ts} & L_{Te} \cos(\phi) & L_{Tw} \cos(\phi) & 0 \\
-L_{Ts} & 0 & 0 & 0 & L_{Tw}
\end{pmatrix} \dot{\theta}_{23467} = J_{23467} \dot{\theta}_{23467} \] (5.5)

where \( L_{Ts} = \|P_T - P_s\|, \ L_{Te} = \|P_T - P_e\| \) and \( L_{Tw} = \|P_T - P_w\| \).

Assuming that \( L_{Tw} = L_{Te}/10 \) considering the practical arm dimension, Eq. 5.4 can be simplified as

\[ J_{23467} \cdot J_{23467} = \begin{pmatrix}
\frac{101}{100} L_{Te}^2 \sin \phi^2 & -\frac{101}{100} L_{Te}^2 \sin \phi \cos \phi & 0 \\
\frac{101}{100} L_{Te}^2 \sin \phi \cos \phi & L_{Ts}^2 + \frac{101}{100} L_{Te}^2 \cos \phi^2 & 0 \\
0 & 0 & \frac{1}{100} L_{Te}^2 + L_{Ts}^2
\end{pmatrix} \] (5.6)

\[ \approx \begin{pmatrix}
L_{Te}^2 \sin \phi^2 & -L_{Te}^2 \sin \phi \cos \phi & 0 \\
-L_{Te}^2 \sin \phi \cos \phi & L_{Ts}^2 + L_{Te}^2 \cos \phi^2 & 0 \\
0 & 0 & L_{Ts}^2
\end{pmatrix} \] (5.7)

\[ = \begin{pmatrix}
(L_{we} + L_{Tw})^2 \sin \phi^2 & -(L_{we} + L_{Tw})^2 \sin \phi \cos \phi & 0 \\
-(L_{we} + L_{Tw})^2 \sin \phi \cos \phi & L_{Ts}^2 + (L_{we} + L_{Tw})^2 \cos \phi^2 & 0 \\
0 & 0 & L_{Ts}^2
\end{pmatrix} \] (5.8)

where \( \frac{101}{100} L_{Te}^2 \approx L_{Te}^2 \). Considering the fact that \( L_{Te} = L_{we} + L_{Tw} \) and \( L_{Tw} < < L_{we}, L_{Te} \) in Eq. 5.6
can be approximated as $L_{we}$. In addition, $L_{T_S} \approx L_{W_S}$ in most of the work space. Thus we have

$$
J_{23467} \cdot J_{23467}^* \approx \begin{pmatrix}
(L_{we} + L_{Tw})^2 \sin \varphi^2 & -(L_{we} + L_{Tw})^2 \sin \varphi \cos \varphi & 0 \\
-(L_{we} + L_{Tw})^2 \sin \varphi \cos \varphi & L_{T_S}^2 + (L_{we} + L_{Tw})^2 \cos \varphi^2 & 0 \\
0 & 0 & L_{T_S}^2
\end{pmatrix}
$$

$$
\approx \begin{pmatrix}
L_{we}^2 \sin \varphi^2 & -L_{we}^2 \sin \varphi \cos \varphi & 0 \\
-L_{we}^2 \sin \varphi \cos \varphi & L_{W_S}^2 + L_{we}^2 \sin \varphi^2 & 0 \\
0 & 0 & L_{W_S}^2
\end{pmatrix} = J_{234} \cdot J_{234}^* \quad (5.9)
$$

Therefore the singular value decomposition of $J_{23467} \cdot J_{23467}^*$ results in the approximately same manipulability ellipsoid profile based on $J_{234} \cdot J_{234}^*$. It implies that the manipulability concept approach based on the seven DOF arm model does not reveal the wrist orientation effect on the redundancy of the human arm. Therefore it is necessary to utilize the different analysis technique to establish the redundancy resolution model as a function of the wrist orientation.

### 5.1.2 Types of wrist orientation change for the given task

An excessive rotation of specific joint can create the other joint movement due to the muscular coupling. In this context, muscular coupling in the human arm can play an important role in the redundancy resolution of the human arm movement. In order to relate the muscular coupling on the wrist to the redundancy of the human arm, we first formulate the relationship between the wrist orientation change and its effect on the swivel angle for the given target location as follows:

$$
T_\varphi T_{\theta_5} T_{\theta_6} T_{\theta_7} s_{st} = s_{target} \quad (5.10)
$$

90
Figure 5.2: Wrist orientation and the swivel angle: (a) Simplified arm model for the fixed wrist position (b) Rotation of the wrist to reach target and the swivel angle to avoid the joint (c) Joint angle availability function $C_{in}$ and $C_{out}$ defined on the wrist and corresponding swivel angles

where $\phi$ is the desired swivel angle for the given wrist position based on the kinematic constraint in the previous section and $g_{target}$ is the desired wrist orientation and position at the target location. Assuming that the wrist is already close enough to the target, only the wrist orientation change can make the center of the wrist $P_T$ reach the desired position along the sphere surface created by utilizing the three wrist joints ($\theta_5$, $\theta_6$, and $\theta_7$) and the swivel angle $\phi$ [Fig. 5.2(b)] rotation. Given the joint limit of the wrist $\theta_5$, $\theta_6$, and $\theta_7$ in our seven DOF arm model, there can be two types of motion planning for Eq. 5.10 without moving the wrist position.

5.1.2.1 Case 1:

Inverse kinematic solution to Eq. 5.10 exists for $\{\theta_5, \theta_6, \theta_7\}$ within the joint limits for the fixed wrist position. In this case, the given task can be done easily without causing the uncomfortable feeling on the wrist. So there is no swivel angle changes.
\[ T_{\phi_{eq}} T_{\theta_5} T_{\theta_6} T_{\theta_7} g_{st} = g_{\text{target}} \]  

(5.11)

5.1.2.2 Case 2:

Inverse kinematic solution to Eq. 5.10 exists for \( \{\theta_5, \theta_6, \theta_7\} \) outside the joint limit for the fixed wrist position. Since one of the joint exceed the joint limit, the swivel angle needs to be changed to maintain \( \{\theta_5, \theta_6, \theta_7\} \) within the corresponding joint limits[Fig. 5.2(b)]. Eq. 5.12 describes this case.

\[ T_{\phi_{eq} + \Delta \phi} T_{\theta_5} T_{\theta_6} T_{\theta_7} g_{st} = g_{\text{target}} \]  

(5.12)

where \( \Delta \phi \) is the deviation from the equilibrium status of the swivel angle, \( \phi_{eq} \). The Eq. 5.12 can be rewritten as

\[ T_{\theta_5} T_{\theta_6} T_{\theta_7} g_{st} = T_{\phi_{eq} + \Delta \phi}^{-1} g_{\text{target}} \]  

(5.13)

Effectively, \( T_{\phi_{eq} + \Delta \phi}^{-1} \) on the right side of Eq. 5.13 moves the target within the work space of the wrist.

Unlike the conventional robots, human arm has an unique muscular and skeletal structure which make each arm segment moves jointly. For instance, when the wrist rotates to pour the water into the cup, one of the wrist joints represented in the seven DOF arm model[Fig2.2(a)] can reach the joint limit due to the limited range of the motion. Thus one starts to feel uncomfortable with resistance and use other joints (upper arm) to finish the task. Human motor
control prefers to choose the joint configuration which avoids the joint limit of each joint. To quantify how much all joints approach the joint limit in aggregate, the joint angle availability function[72, 71, 87] can be considered as follows:

\[
C = \sum_{i=1}^{n} w_i \left( \frac{\theta_i - \theta_{i\text{ref}}}{\Delta \theta_i} \right)^2
\]  
(5.14)

where \(\Delta \theta_i = (\max \theta_i - \min \theta_i)/2\) is the range of each joint, \(\theta_{i\text{ref}} = (\max \theta_i + \min \theta_i)/2\) is the neutral position of each joint and \(W_i\) is the weighting coefficient that reflects the different effect on \(C\) in Eq. 5.14. This function has the following property. When \(\theta_i\) approaches the joint limits which are \(\max \theta_i\) or \(\min \theta_i\) in Eq. 5.14, \(C\) becomes \(\sum_{i=1}^{n} w_i\). When \(\theta_i\) approaches the \(\theta_{i\text{ref}}\) in Eq. 5.14, \(C\) becomes zero. Thus the \(C\) is ranged over \([0 \sum_{i=1}^{n} w_i]\). In order to relate the wrist orientation to the swivel angle, we can selectively focus on the joint availability function output on the wrist in Eq. eq: ergodic2, modified from Eq. 5.14 and relate this to the swivel angle change.

\[
C = w_1 \left( \frac{\theta_5 - \theta_{5\text{ref}}}{\Delta \theta_5} \right)^2 + w_2 \left( \frac{\theta_6 - \theta_{6\text{ref}}}{\Delta \theta_6} \right)^2 + w_3 \left( \frac{\theta_7 - \theta_{7\text{ref}}}{\Delta \theta_7} \right)^2
\]  
(5.15)

### 5.1.3 Joint availability function function and the swivel angle

The modified joint angle availability function in Eq. 5.15 quantitatively defines how much the wrist joints approach the joint limit in aggregate. Then it is possible to map this specific function output to the corresponding swivel angle as a function of wrist orientation and this mapping enables more generalized human motor control model, which is applicable to the exoskeleton robot control. In order to formulate the human motor control model, the following three conditions were considered between the modified joint angle availability function output
Once the availability function output reach the maximum value $\sum_{i=1}^{n} w_i$ or minimum value $0$, the deviated swivel angle $\Delta \phi$ should be saturated to its maximum or minimum value.

2. The proper weighting coefficient $w_i$ for each wrist joint should be estimated considering the different effect of each wrist joint on the swivel angle.

3. Asymmetric muscular structure of human arm having different muscular tension needs to be considered: we defined two regions where $\phi_{fin} \leq \phi_{ref}$ and $\phi_{fin} > \phi_{ref}$. In each region, it is assumed that there is a different mapping between swivel angle $\Delta \phi$ and the joint availability function as shown in Fig 5.5.

The simplest form of relation will be the linear mapping of the joint angle availability function as shown in Fig 5.3. The alternative choice can be a non linear sigmoid function as shown in Fig. 5.4. Since the sigmoid function has an advantage against the linear mapping which comes from the fact that the output of the sigmoid function approaches an asymptotic
Figure 5.4: Non-linear mapping based on sigmoid function between the joint availability function and swivel angle change. The modified sigmoid function was scaled and shifted from the basic form of sigmoid function bound in a closed form and there is no abrupt transition in the function output, we adopted sigmoid function to our application. The basic form of sigmoid function is modified to map the joint availability function output to the corresponding swivel angle as shown in Fig. 5.4.

\[
\Delta \phi = \frac{\Delta \phi_{\text{max}}}{1 + e^{-12(c/c_{\text{max}} - 0.5)}}
\]

\[
\Delta \phi_{\text{max}} = \begin{cases} 
\phi_{\text{ref}} - \min(\phi_{\text{fin}}) & , \phi_{\text{fin}} \leq \phi_{\text{ref}} \\
-\phi_{\text{ref}} & , \phi_{\text{fin}} > \phi_{\text{ref}} 
\end{cases}
\]

where \(\phi_{\text{ref}} \leq 0\) and \(\min(\phi_{\text{fin}}) \leq 0\) based on our swivel angle definition in Fig. 5.5. Note that Eq. 5.16 is separately defined depending on the swivel angle \(\phi_{\text{fin}}\). Then by combining Eq. 5.15
Figure 5.5: Deviated swivel angle $\Delta \phi (\Delta \phi_u, \Delta \phi_d)$ from $\phi_{ref}$ in two swivel angle range: $\phi_{fin} \leq \phi_{ref}$ and $\phi_{fin} > \phi_{ref}$.

with Eq. 5.16 for either $\phi_{fin} \leq \phi_{ref}$ or $\phi_{fin} > \phi_{ref}$, we have

$$
\frac{C}{C_{max}} = -\frac{1}{12} \log \left( \frac{\Delta \phi_{max}}{\Delta \phi} - 1 \right) + 0.5
$$

$$
= \frac{w_1}{C_{max}} \left( \frac{\theta_5 - \theta_{5,ref}}{\Delta \theta_5} \right)^2 + \frac{w_2}{C_{max}} \left( \frac{\theta_6 - \theta_{6,ref}}{\Delta \theta_6} \right)^2
\quad + \frac{w_3}{C_{max}} \left( \frac{\theta_7 - \theta_{7,ref}}{\Delta \theta_7} \right)^2
$$

$$
\Rightarrow C' = w'_1 \theta'_5 + w'_2 \theta'_6 + w'_3 \theta'_7
$$

(5.17)

(5.18)

where $C' = \frac{C}{C_{max}}$, $w'_i = \frac{w_i}{C_{max}}$ and $\theta'_i = \left( \frac{\theta_i - \theta_{i,ref}}{\Delta \theta_i} \right)^2$. To estimate $w_i$ in Eq. 5.18, the kinematic data from the multiple subjects were collected by using the motion capture system for the specific tasks that require the wrist orientation changes. By using the joint angle information, Eq. 5.18...
can be extended as

\[
C'(t_0) = w'_1 \theta'_5(t_0) + w'_2 \theta'_6(t_0) + w'_3 \theta'_7(t_0)
\]

\[
C'(t_1) = w'_1 \theta'_5(t_1) + w'_2 \theta'_6(t_1) + w'_3 \theta'_7(t_1)
\]

\[
\vdots
\]

\[
C'(t_{N-1}) = w'_1 \theta'_5(t_{N-1}) + w'_2 \theta'_6(t_{N-1}) + w'_3 \theta'_7(t_{N-1})
\] (5.19)

Then the matrix representation of Eq. 5.19 is given by

\[
C = E \cdot W
\] (5.20)

\[
C = \begin{bmatrix} C'(t_0) & \ldots & C'(t_{N-1}) \end{bmatrix}^T, \quad W = \begin{bmatrix} w'_1, w'_2, w'_3 \end{bmatrix}^T
\]

\[
E = \begin{pmatrix} \theta'_5(t_0) & \theta'_6(t_0) & \theta'_7(t_0) \\
\theta'_5(t_1) & \theta'_6(t_1) & \theta'_7(t_1) \\
\vdots & & \\
\theta'_5(t_{N-1}) & \theta'_6(t_{N-1}) & \theta'_7(t_{N-1}) \end{pmatrix}
\]

Since \( \sum_i w_i^2 \) should be bounded by some constant, an additional constraint is necessary to Eq. 5.20. Without loss of generality \( \sum_i w_i^2 = 1 \) can be applied to Eq. 5.20 as a regulation factor.

Then Eq. 5.20 is reformulated as

\[
\rightarrow \hat{W} = \min[\|C - E \cdot W\|^2 + \lambda \|w\|^2]
\] (5.21)

The solution to Eq. 5.21 is well known in many literature\[115]\[35\] and the closed form solution
to Eq. 5.21 is given by

\[ \hat{\mathbf{W}} = (\mathbf{E}^T \mathbf{E} + \lambda \cdot \mathbf{I})^{-1} \mathbf{E}^T \cdot \mathbf{C} \] (5.22)

where \( \lambda \) is iteratively found to make \( \| \mathbf{W} \|^2 = 1 \) based on the matlab simulation. Then the swivel angle estimation model as a function of wrist orientation is fully defined.

Once all the joint angles are collected from a specific subject, \( \mathbf{C} \) [Eq. 5.17] and \( \mathbf{E} \) as a function of swivel angle and joint angles can be constructed to estimate \( \mathbf{W} \) based on Eq. 5.22. Once \( \mathbf{W} \) is estimated, it can be imported to the robot controller to compute \( \frac{\mathbf{C}}{\ell_{\text{max}}} \) based on Eq. 5.20. Then by plugging \( \frac{\mathbf{C}}{\ell_{\text{max}}} \) into Eq. 5.16, \( \Delta \phi \) can be achieved. Note that as mentioned above, the whole estimation process were individually defined for two cases where \( \phi_{\text{fin}} \leq \phi_{\text{ref}} \) and \( \phi_{\text{fin}} > \phi_{\text{ref}} \) for more precise estimation result.

### 5.2 Experimental setup

The proposed swivel angle estimation model requires the parameter estimation respectively for \( \phi_{\text{ref}} \) and \( \Delta \phi \). In order to verify the proposed swivel angle estimation model, the kinematic data of the human arm is collected using the Phasespace motion capture system (Phasespace, Inc.). Active LED makers were attached to a subject’s body at key anatomical locations as shown in Fig. 3.4.

Since \( \phi_{\text{ref}} \) is defined by the wrist position, the experimental setup for \( \phi_{\text{ref}} \) does not include the wrist orientation changes. On the other hand for \( \Delta \phi \) estimation, wrist positions were fixed at the specific position and subjects were requested to only change the wrist orientation to minimize the wrist position effect. In the following section, we introduce two experimental
setup to estimate $\phi_{ref}$ and $\Delta \phi$.

5.2.1 Experiments for swivel angle base on the wrist position

In order to define $\phi_{ref}$ for the unconstrained reaching tasks, three types of reaching tasks introduced in Fig. 3.5(a) and Fig. 3.5(b) were given to the subjects. Five right handed healthy subjects participated in the experimental protocol. Of the five subjects, three were males and two were females. Each subject was tested in a three different sitting posture with his/her torso restrained from torsional movements. The distance between the subject and the table was adjusted based on the length of the subject’s arm in order to avoid a full stretch of the arm (singular configuration). The rest of the estimation steps and performance evaluation process are same as those introduced in Section 3.2.

5.2.2 Experiments for swivel angle base on the wrist orientation

In order to define the effect of wrist orientation on $\Delta \phi$, subjects were requested to reach specific target positions in Fig. 5.6 and then change the orientation of the wrist. To precisely locate the subject’s hand on the desired position and help subjects find the target location in the space, a six-DOF industrial robot (DENSO) was programmed to project laser on the target location as shown in Fig. 5.6. Thus subjects visually know where to put there wrist in the space by looking at the laser mark projected on their wrist. There are two different body positions and in each position there are three different target locations. Considering the most frequent activities of daily life such as rotating the door knob and pouring the water, subjects were asked to rotate wrist inward and outward five times as if he rotates the door knob. Using
Figure 5.6: Experimental setup to estimate $W$. Subjects are requested to face the front in two different postures where the torso is not rotated (a) and rotated by 45 degree (b). For each torsional configuration, they place the hands in three different locations. In order for this, we used six axis Denso robot that has a laser pointer at the tool frame. Denso places the laser pointer in parallel with target point and project laser to one of the target locations ($P_{m1}, P_{m2}, P_{m3}, P_{d1}, P_{d2}, P_{d3}$).

This kinematic data, Eq. 5.22 will be solved to estimate $W$. However note that the proposed experimental setup does not represent all possible wrist oriented tasks. To reveal more general relationship between the wrist orientation and the swivel angle, other types of tasks need to be considered to estimate $W$. For the practical reason, we only focused on the specific wrist orientation changes.

Similarly from $\phi_{ref}$, the computed swivel angle change ($\phi_{act} - \phi_{ref}$) based on the collected kinematic data were compared with estimated swivel angle change $\Delta \phi$ estimated by Eq. 5.16. Fig 5.7 shows the direct comparison result and the estimation error at six different target positions is summarized in Table. 5.1. In addition, the statistical analysis for the weighting coefficients $W$ were plotted as the box plot[Fig. 5.8] to see the relative effect of each wrist joint.
on the swivel angle for the given tasks.

Table 5.1: Averaged absolute differences between measured and estimation swivel angles

<table>
<thead>
<tr>
<th>Sub</th>
<th>$P_{m1}$</th>
<th>$P_{m2}$</th>
<th>$P_{m3}$</th>
<th>$P_{d1}$</th>
<th>$P_{d2}$</th>
<th>$P_{d3}$</th>
<th>$P_o(y,z)$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.1±8.0</td>
<td>7.1±7.0</td>
<td>16.9±10.8</td>
<td>2.1±8.6</td>
<td>9.2±8.2</td>
<td>6.2±11.0</td>
<td>(-160, 280)</td>
</tr>
<tr>
<td>2</td>
<td>1.3±7.3</td>
<td>4.5±8.3</td>
<td>6.5±12.0</td>
<td>4.0±14.2</td>
<td>5.0±14.7</td>
<td>16.4±16.5</td>
<td>(-140, 320)</td>
</tr>
<tr>
<td>3</td>
<td>2.1±5.4</td>
<td>3.1±10.9</td>
<td>1.6±8.4</td>
<td>0.7±11.4</td>
<td>4.0±13.8</td>
<td>6.2±10.0</td>
<td>(-160, 390)</td>
</tr>
<tr>
<td>4</td>
<td>3.7±7.3</td>
<td>4.6±7.9</td>
<td>3.9±7.5</td>
<td>0.1±7.9</td>
<td>3.7±7.6</td>
<td>6.0±9.3</td>
<td>(-70, 290)</td>
</tr>
<tr>
<td>5</td>
<td>13.0±32.1</td>
<td>2.8±9.9</td>
<td>0.9±11.3</td>
<td>0.5±9.8</td>
<td>2.5±9.4</td>
<td>2.9±8.11</td>
<td>(-160, 170)</td>
</tr>
</tbody>
</table>

5.3 Result and Conclusion

The goal of this study was to propose a closed form redundancy resolution mechanism of the human arm as a viable control scheme for an exoskeleton robot. The criteria for resolving the human arm redundancy was experimentally verified and validated for an wearable robotic application. It is shown in Table 5.1 that the averaged absolute error between measured and estimated swivel angle is 4.89 degree for $\Delta \phi$. The direct comparison result in Fig. 5.7 and Fig. 3.9 also shows that not only the low averaged error but also the high correlation between the estimated and measured swivel angle are observed. For the swivel angle estimation based on the wrist orientation, joint availability function was employed and the result in Fig. 5.8 shows that $w_1'$ has a dominant effect on $\Delta \phi$ while $w_3$ is the least dominant. Since $w_1'$ is for the rotation around joint five at the wrist, it implies that the muscular coupling between joint five and the swivel angle is stronger than other joint couplings for the given tasks in our experiment. Summarizing all the result so far, we can conclude that for most of the unconstrained reaching and grasping tasks with wrist orientation changes, swivel angle can be successfully reproduced.
Figure 5.7: Swivel angle as a function of wrist orientation. The first ((a), (c), (e)) and second ((b), (d), (f)) column show the comparison result between the estimated and measured swivel angle for subject 1 at $P_{m1}$ and $P_{d1}$ respectively. The first row data is $\theta_5(t)$, $\theta_6(t)$ and $\theta_7(t)$ on the wrist which are the input to the swivel angle estimation algorithm. The second row shows the comparison result between the estimated and measured swivel angle at $P_{m1}$ and $P_{d1}$. The third row plots the estimated swivel angle versus measured swivel angle.
Figure 5.8: Statistical analysis of weighting coefficient to define the joint angle availability function. The mean and variance of the weighting coefficient (a) when the rotation around joint five is negative (wrist rotation toward body), b) when the rotation around joint five is positive.

In a forward kinematic of the robotic manipulator that has the same degree of freedom such as EXO-UL7, the swivel angle is mathematically represented as a function of shoulder joints which is connected to the heavy links and structure than those of other joints. In general, the wearer should overcome the relatively high friction and inertial dynamic without any compensation mechanism. Since the weight of the robotic link on the wrist is lighter than any other arm links, relating the wrist position and orientation to the swivel angle can be exploited as an efficient and convenient control algorithm to improve the transparency between wearer and the exoskeleton robot. Fig. 5.9 shows the controlled arm configuration for the given wrist position with different wrist orientation changes.

In addition, the proposed algorithm computes all the important parameters for the controller in off-line and imports the pre-determined parameters to the controller such that it
is computationally efficient. Eventually the inverse kinematics as a function of wrist joint angles provides the stable and closed form solution that does not require the iterative operation. However, note that although the current experiment setup to verify the proposed redundancy resolution scheme is enough for the pilot study, it should be improved to have more clear insight into the relationship between the robot and the human motor control.
Part III

Third Part
Chapter 6

Stroke patient rehabilitation

6.1 Rehabilitation based on the exoskeleton robot

The rehabilitation-induced recovery of motor function in chronic stroke patients has attracted great interest due to its importance in the patient’s quality of life[48][47]. Especially, recent improvement in brain mapping techniques such as TMS, PET, and fMRI facilitate researchers to have deeper understanding of brain plasticity. The most interesting and important evidence that has been revealed is that immediate and injury related motor cortex reorganization in patient’s brain can be significantly affected by the post-stroke motor experience in the chronic stroke phase[94][95]. Then the important question is that what types of rehabilitative training administered after stroke improve the plasticity of the brain most. The proper intervention strategies based on sound motor control and learning principles can provide maximal recovery for the chronic stroke patients[48][47][94][95][11]. In the following section, we will introduce the clinical trial result for the stroke patient rehabilitation based on the upper limb.
Recently the advent of robot-assisted rehabilitation treatment has shown that the robotic system can be a useful tool for the patients suffering from a wide spectrum of neuromuscular disorders such as stroke, spinal cord injury, and muscular dystrophy[92][88][65][118]. Regardless of the successful work in many research area, they may be subject to the following main deficiencies: (1) to the best of our knowledge there is no seven DOF upper limb exoskeleton robot developed to provide the bilateral as well as unilateral movement training, (2) the assistive control schemes in the rehabilitation program do not consider the redundant nature of the human arm movement and (3) there is no objective evaluation metric that can measure the rehabilitation progress in a fine-scale.

The proposed work in this section tried to accommodate all the deficiencies described above and presents the clinical trial result as well as the complete description of the rehabilitation system model.

### 6.2 Types of rehabilitation

As mentioned above, it is important to provide the patients with the best rehabilitation program to maximize the therapeutic effect in a limited time window. However it is still controversial among the scientist to decide which type of rehabilitation is the most effective in terms of time and cost. In this section, we introduce the most well known and distinguishing rehabilitation schemes which have been applied to the stroke patient clinical trial based on the upper limb exoskeleton robot.
Figure 6.1: Patients during the Unilateral and Bilateral movement training in University of California, San Francisco a) Unilateral movement group patient with paretic limb on his left side and b) Bilateral movement group patient moving both arms

6.2.1 Unilateral movement training

The most well known and widely tested motor rehabilitation scheme is unilateral movement therapy. In this rehabilitation scheme, therapist encourages use of the hemiplegic limb of the stroke patient. The most common type of unilateral type therapy is the constraint-induced movement therapy that showed some success in expediting progress toward recovery of upper limb function[70][73][26]. In this type of therapy, the patient’s intact limbs are constrained by a harness to prevent it from moving while the paretic limb is interacting with therapist or outer environment[21][22][23]. This is because the patients try to compensate the movement of the uncomfortable limb by moving the other limbs. Obviously patients will less use the impaired limb than the intact limb. So far many of the robot based rehabilitation therapy have been done based on the unilateral movement training[65][42][64].
6.2.2 Bilateral movement training

Recently, an alternative rehabilitation approach known as the bilateral movement training has been proposed. The bilateral movement training is to promote the functional recovery of the impaired limb by using the intact limb at the same time. Based on the studies of the interlimb coordination in healthy adults[48], it is known that the bilateral movement training can promote the functional recovery of the impaired limb by exploiting the coupling effect between the upper limbs. During the symmetric and bilateral movement of the limb, what’s happening inside brain is that the intact hemisphere interacts with the damaged hemisphere such that this type of brain stimulation might result in the improved therapy result. There are couple of research result about the effectiveness of the bilateral movement training. Mudie and Matyas[79][80] performed 30-40 sessions of bilateral movement training on twelve chronic stroke patients who were treated by the unilateral movement training previously and demonstrated the significant effect of the bilateral movement training. Although an attempt to replicate the similar level of effectiveness did only show the limited success with six acute and chronic patients[33], other studies have reported positive results using the combination of bilateral training protocol, activepassive movements[103], synchronous and alternating movements with rhythmic auditory cuing[46][98][3], and bilateral movements with neuromuscular stimulation of the impaired arm[49][50][51]. The limitation of the studies described above is that they employ the combination of different training schemes for the patient such that it is not possible to compare the performance of the bilateral movement training with unilateral movement training[79][80][33]. The recent work by [105] presented the direct comparison result between
unilateral and bilateral training protocols. In this research, the effect of bilateral training following a short six sessions of training duration was tested and reported that the bilateral training showed a positive effect when the subjects are exposed to the number of bilateral trainings ranging from six [49][50][51] to 40[79].

6.3 System model

The entire rehabilitation system is described in Fig. 6.2(a). The rehabilitation robotic system is composed of three major parts which are UL-EXO7 exoskeleton robot, control algorithm and video games that interact with UL-EXO7. UL-EXO7 Control PC controls the motion controller to motorize the UL-EXO7 based on the XPC/Host-Target interface and all the sensory inputs from the UL-EXO7 are transmitted to the game PC [Fig. 6.2(a)] through the UDP protocol to minimize the data transmission latency among systems. There are eight different games in the game PC which are joint movement, flower, paint, reach, pong, circular pong, pinball and hand ball games. They are programmed using the Microsoft Robotic Developer Studio 2008[1].
The patients can manipulate the objects in each game by moving a specific joint or the whole arm of the robot. The virtual interaction between the game and the patients are feedbacked to the UL-EXO7 Control PC to create the proper haptic interaction between the robot and patients.

6.4 Rehabilitation based on upper limb exoskeleton

UCSC bionics lab have collaborated with UCSF neural rehabilitation medical center for the short term clinical trial research. In order for this, the seven DOF upper limb exoskeleton robot was installed in the UCSF medical center and under the supervision of physical therapists, robot assisted physical therapy was applied to both unilateral and bilateral movement training groups. Each training group consists of five stroke patients in a chronic phase and they participated in the research twice a week for six weeks. Among them, two patients could not finish the total of twelve sessions for six weeks because of their personal schedule.

To facilitate the therapy effect and assess the improvement objectively, eight different games were developed. As a protocol, all the patients spent two hours for playing the games a session. Due to the fundamental difference between the unilateral and bilateral movement training method, each patient group experienced different combination of assistive control schemes. In the following session, we describe all the control schemes applied to the current rehabilitation program as well as the description about the games. During the therapy, all the kinematic data as well as the force/torque signal were recorded through the UDP protocol defined between the robot and control PC. After the therapy, we analyze the patient's kinematic data based on a couple of evaluation metrics that can reveal the various aspect of the rehabilitation effect. Since
the research is only done for a limited number of subjects, we do not conclude what type of the therapy is better than the other therapy and the conclusion will be remained as a future work.

### 6.4.1 Control schemes applied to the rehabilitation research

There are total of four control schemes made for the rehabilitation robotic system. Table 6.1 summarize the proper combination for each movement training group. The detailed description of each control scheme will be shown next. Note that the admittance control scheme was excluded due to the safety problem. Normally stroke patients have their upper limb adducted to the trunk and suffer wrist contracture. It implies that stroke patients consistently apply force to the force/torque sensor such that the admittance controller keeps pushing the arm to the trunk. Thus the additional safety mechanism such as force field around the patient is necessary.

Table 6.1: The combination of control schemes

<table>
<thead>
<tr>
<th>Therapy type</th>
<th>Gravity Comp</th>
<th>Friction comp</th>
<th>Force Field</th>
<th>Master-Slave</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unilateral</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Bilateral</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

### 6.4.1.1 Gravity compensation

The dynamic equations of robot motion characterizes the following time varying response of a system given external influences and initial states. Although dynamics of the robot are highly non-linear and complex, under the assumption of rigid body dynamics all open chain
manipulators can be formulated as:

\[ \tau = M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + N(\theta, \dot{\theta}) \quad (6.1) \]

where

- \( \tau_{n \times 1} \) is the actuator torque vector
- \( \theta_{n \times 1} \) is the joint position vector
- \( M_{n \times n} \) is the manipulator inertia matrix
- \( C_{n \times n} \) is the Coriolis matrix
- \( N_{n \times 1} \) includes the gravitational terms and other external forces
- \( n \) is the number of joints

Only the \( N(\theta) \) term in Eq. 6.1 is required for the gravity compensation[81]. Assuming that the angular velocity and the acceleration of the joint angles are negligible for the human arm movement, compensating the gravity can resolve the most of the human arm dynamic such that gravity compensation becomes the background control scheme for the exoskeleton control.

### 6.4.1.2 Friction compensation

It is well known that friction depends on both velocity and position, but it’s hard to establish the general model to explain this phenomenon especially at low velocity[109]. Thus considering the computational efficiency and the stability of the control algorithm, the basic form of coulomb friction model[109] is employed as a friction compensation algorithm. To prevent the ambiguity at zero velocity, the individual joint torque for friction compensation is given by a following linear model in Fig. 6.3(a). The friction in the range of \( \dot{\theta} \leq \dot{\theta}_{\text{guard}} \) is modelled as a linear function considering the practical implementation and \( \dot{\theta}_{\text{guard}} \) is chosen experimentally for each joint.
Figure 6.3: a) The simplified Coulomb friction model which is modified to prevent the ambiguity at the zero velocity. The friction within $\dot{\theta}_{\text{guard}}$ is modelled as a linear function considering the practical implementation and $\dot{\theta}_{\text{guard}}$ is empirically chosen. The practical system has 0.01 for the $\dot{\theta}_{\text{guard}}$ and b) The force field generation mechanism based on the given wrist position and the swivel angle estimation.

6.4.1.3 Force fields with swivel angle estimation

In the robot-assisted rehabilitation therapy, providing an assisting force is necessary and important. For the specific game, robot provides an assistive force by creating a force field based on the target location and current end-effector position such that patient can move their affected arm toward the target in the virtual environment. Fig. 6.3(b) describe the force field generation mechanism for the given end-effector position. Due to the redundant nature of the seven DOF robot, the relative position of the hand with respect to the target location can not be directly translated to the assistive force without properly defining the redundancy of the seven DOF exoskeleton robot, which can be parameterized by the swivel angle. Thus for the specific type of the game, swivel angle estimation based on Eq. 3.28 was applied to the force field generation block described in Fig. 6.3(b), which is a position based impedance control.
6.4.1.4 Master-Slave control

For the bilateral movement training, intact limb assists the paretic limb. In order to support this mechanism, desired joint angles are transmitted from the intact limb (Master) to the paretic limb (Slave). The difference of the joint angle between the master and slave side is fed into the PD controller to create the joint torque on the slave side. Since forcing slave side to be completely symmetric with master side can harm the patient’s contracted muscle on the affected limb, the joint torque on the slave side is limited.

6.4.2 Types of Games

There are total of eight different games designed for the rehabilitation program, which are flower, paint, joint movement, reach, pong, pin ball, hand ball and circular pong game. Especially flower, paint, joint movement and reach game are designed for not only the therapy but also the rehabilitation assessment. The rest of the games are purely therapeutic games. All the participants played the game for two hours in their visit to the UCSF medical center under the supervision of a physical therapist. Detailed description for each game will be given in the following section.

6.4.2.1 Flower game

Flower game is composed of eleven different configurations where targets are placed symmetrically as shown in Fig. 6.4. In each target configurations, patients are instructed to touch the blue ball at the center of the screen first and the farthest red ball as their hands follow the straight line. To go to the next target configuration, they touch the blue ball at the center
Figure 6.4: Flower game: a) targets on the horizontal line, b) targets on the horizontal line which is rotated by 90 degrees, c) targets on the vertical lines, d) through k) have targets on the V shaped lines and targets are rotated by 45 degree in each configuration.
Figure 6.5: Paint game: Red balls turn into green ball when touched by the hand.

again. For the unilateral movement training group, patients only touch the targets which are on the same side as their affected limb while bilateral movement training group reach all the targets at the same time. The unilateral movement training group patients are supported by the force filed such that there is a weak assisting force toward target which helps patient follow the desired path.

6.4.2.2 Paint game

In this game, the small balls are created spherically around the robot. When patients touch the balls, the red ball turns into the green ball as shown in Fig. 6.5. The ratio of green balls and red balls can be used to assess the patient’s mobility improvement. The therapist can freely set up the radius at which the balls are created considering the patient’s impairment level. The default radius defined as the distance between the target balls and the center of the body is 50cm.
Figure 6.6: Joint movement game: Directly measures the range of each joint for seven different configurations. a) shoulder abduction-adduction, b) should flexion-extension c), shoulder rotation, d) elbow flexion-extension, e) wrist pronation-supination, f) wrist flexion-extension and g) wrist radial-ulnar deviation.
Joint movement game

Joint movement game is a purely diagnostic game which measures the range of motion for each joint. This game is composed of the shoulder abduction-adduction, shoulder flexion-extension, shoulder rotation, elbow flexion-extension, wrist pronation-supination, wrist flexion-extension and wrist radial-ulnar movement as shown in Fig. 6.6.

Reach game

In this game, target balls are created on the plane at the height of the waist as shown in Fig. 6.7. When players reach the target balls in the air, they drop to the floors. This game is also classified as the diagnostic game since it is well structured and has a fixed target locations. In case of the bilateral movement training group patients, they use both hands to drop all the balls while the unilateral movement training group patients only drops the half of the balls depending on the side of paretic limb.

Figure 6.7: Reach game: Patients reach targets to drop the ball to the floor.
6.4.2.5 Handball game

In the handball game, patient hit the bouncing ball as shown in Fig. 6.8. The bilateral movement group patients move both arms symmetrically to block the ball while the unilateral patient group only use the paretic limb. For the unilateral patients, bounced ball tends to come to the paretic limb side. This game is purely therapeutic game.

6.4.2.6 Pong game and Circle game

In the pong game[Fig. 6.9(a)], patients compete with the virtual opponent by blocking the ball and returning it back to the opponent. The circle game[Fig. 6.9(b)] is similar to the pong game except that circle game moves paddles along the circumference of the cylinder and the ball comes back to the player after it is bounced back from the front wall. The bilateral group patient use two paddles symmetrically and unilateral group patients use only one paddle to block the ball. In both games, players can choose the specific joint or the end effector position as a control method. For example, patients can use the minimum and the maximum joint range.
of the wrist as the leftmost and rightmost position of the paddle. Therapist determines which control mechanism is proper for each patient.

6.4.2.7 Pin ball game

This game is exactly same as the traditional pinball game. The control mechanism is the most important part. Bilateral movement training group patients have to move both flippers simultaneously using the control joints while the unilateral movement training group patients use both flippers using only the affected limb. Similarly from the pong game, patients can choose the control joints depending on the stroke type such that the range of the specific joint is mapped into the range of the paddle movement.

6.5 Experiment

Total of ten Patients participated in the research and they either belong to the unilateral or bilateral movement training groups. The therapy program for each training group is described
in the Table. 6.2. For the total of twelve sessions, patient commonly played the default session defined in the Table. 6.2. Then according to their number of visit to UCSF, they interchangeably played either odd session or even session therapy program. Note that the unassisted flower game in the even session program is the flower game that does not provide the assistive force to the patients except the gravity and friction compensation. Since the flower game provides the well-structured target configuration which regularly covers the entire work space of the human arm with desired path, it is suitable for the rehabilitation assessment without assisting force from the robot. The therapy programs introduced here is carefully chosen by the physical therapist group in UCSF. In addition, all the therapy process had been thoroughly monitored by the therapist in UCSF.

Table 6.2: Therapy game program

<table>
<thead>
<tr>
<th>Session</th>
<th>Program</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default session</td>
<td>Flower → Joint movement → Paint → Reach</td>
</tr>
<tr>
<td>Odd session</td>
<td>Pong → Pinball → Paint</td>
</tr>
<tr>
<td>Even session</td>
<td>Circle → Handball → Unassisted flower.</td>
</tr>
</tbody>
</table>
6.5.1 Evaluation metrics

During the entire therapy process, all the joint angle data from all subjects can be measured in realtime. Since one of the advantages for the robot assisted physical therapy over the traditional physical therapy is the capability to assess the patient’s progress objectively in a fine scale, we introduce a couple of performance evaluation metrics adopted in this research. There are total of five metrics which are range of motion, travel distance, relative achievement, area around the straight line and instantaneous efficiency. Depending on the characteristic of the therapy game, the different combination of metrics are employed as shown in the Table. 6.3.

<table>
<thead>
<tr>
<th>Game Type</th>
<th>ROM</th>
<th>TD</th>
<th>AR</th>
<th>IE</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flower</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paint</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reach</td>
<td>√</td>
<td></td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint movement</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

ROM: Range of Motion, TD: Travel Distance
AR: Area of hand trajectory enclosing the desired trajectory
IE: Instantaneous Efficiency, PA: Painted Area

6.5.1.1 Range of Motion

The range of motion is directly measured when the patients play the joint movement game. The metric is simply the range of each joint[Eq. 6.2].

\[
ROM = [\theta(1)_{max} - \theta(1)_{min}, \theta(2)_{max} - \theta(2)_{min}, \ldots \theta(7)_{max} - \theta(7)_{min}]
\]  
(6.2)

where \(\theta(i)_{max}\) and \(\theta(i)_{min}\) is the maximum and minimum value of the \(i^{th}\) joint angle.
6.5.1.2 Painted Area

It simply means the ratio of touched balls and total number of target balls, which is defined only for the paint game. \( PA(s, r) \) is the painted area at session \( s \) and repetition \( r \) of the game where \( s \in \{1, 2, \ldots, 12\} \) and \( r \in \{1, 2, \ldots, R\} \). Note that \( R \), the total number of repetition for the given time can be different between subjects. Then scalar value \( PA_e(s) = \frac{1}{R} \sum_{r=1}^{R} PA(s, r) \) becomes the averaged painted area computed at session \( s \).

6.5.1.3 Travel distance

Travel distance defined in Eq. 6.3 is the integrated travel distance of the patient’s hand in a specific game. The \( TD(s, r) \) in Eq. 6.3 means the travel distance measured at session \( s \) and repetition \( r \) of each game, and \( TD_e(s) \) in Eq. 6.4 is the travel distance averaged over the repetition \( r \). This value will be monitored throughout the entire sessions.

\[
TD(s, r) = \sum_{n=0}^{N-1} \| X(\theta(s, r, n)) - X(\theta(s, r, n-1)) \| \quad (6.3)
\]

\[
TD_e(s) = \frac{1}{R} \sum_{r=1}^{R} [TD(s, r)] \quad (6.4)
\]

where \( X(\theta(s, r, n)) \) is the hand position of the exoskeleton robot at the \( n \)th sampled time index in repetition \( r \) and session \( s \). Note that \( R \) is the total number of repetition done in each session and \( N \) is total number of samples in each repetition. The time duration between adjacent time indices is 1/1024 second, which is the sampling rate of the encoder.
6.5.1.4 Area around straight line

This metric is to measure how much the patient’s hand is deviated from the desired trajectory defined in the assisted and unassisted flower game. Fig. 6.11 depicts the target locations in the flower game. Patients starts to move their hand from the center of the blue ball and to red target ball following the straight line connecting the blue and red ball as much as possible. The end effector position at the $m$th sampling moment is denoted as $X(\theta(m))$ and $X'(\theta(m))$ times $\Delta d(n)$ will be considered as the approximated area around the desired trajectory during the sampling time period. Note that $X'(\theta(m))$ is the position vector projected on the straight line.
line connecting the base position and the target.

\[
AR(s, r, j) = \sum_{n=0}^{N-1} X(\theta(s, r, j, n)) \cdot \Delta d(n)
\]

(6.5)

\[
\Delta d(n) = X'(\theta(s, r, j, n + 1)) - X'(\theta(s, r, j, n))
\]

\[
AR_e(s) = \frac{1}{R} \sum_{r=1}^{R} \left( \frac{1}{11} \sum_{j=1}^{11} AR(s, r, j) \right)
\]

(6.6)

where \( AR_e(s) \) is the averaged \( AR(s, r, j) \) over the 11 different configuration of the flower game and repetition \( r \). Note that \( X(\theta(s, r, j, n)) \) is the end effector position of the robot at the \( n \)th sampling moment, \( j \)th configuration, \( r \)th repetition and \( s \)th session.

### 6.5.1.5 Efficiency Index

Patients after stroke suffer the muscle contraction which results in a limited range of motion for the specific joints such that they learn to compensate uncomfortable joints by moving more intact joints. This is possible because human arm is kinematically redundant and can fulfil the task in different postures. As a result, stroke patients get used to the unnatural movement pattern and never achieve the motor function on their affected limb. It is obvious that compensating the movement can deteriorate the quality of the rehabilitation. Although the previously introduced metrics are useful in monitoring the patients progress for the given task, they do not capture how much patient’s movement becomes natural as other healthy subject. Since one of the key factor in the physical therapy is to make the patients move their arm naturally as other healthy subject, it is important to evaluate the patient’s progress in comprehensive manner.

Under the hypothesis that the natural arm movement of the healthy subjects is efficient for the unconstrained reaching tasks and their redundancy resolution for their arm movement is
Figure 6.12: Averaged range of motion (Shoulder abduction-adduction, Shoulder flexion-extension, Shoulder rotation, Elbow flexion-extension, Wrist pronation-supination, Wrist flexion-extension and Wrist radial-ulnar deviation) and painted area for 12 sessions. The range of motion is plotted with the first (black dotted line) and third (red dotted line) order polynomial fitting while the painted area is plotted with the third order polynomial fitting based on the swivel angle estimation introduced in Section 3.1, efficiency index is developed to measure how much the patient’s arm movement resembles the healthy subject’s arm movement. The proposed metric has two versions depending on the therapy type which are efficiency index for the bilateral and unilateral movement training.

**Efficiency Index for the Bilateral movement training**

Let joint angles from the master and slave side of the robot recorded at time $n$ defined as $\theta_{Sl}(n) = [\theta_{Sl}(1, n), \theta_{Sl}(2, n), \ldots \theta_{Sl}(7, n)]$ and $\theta_{Ma}(n) = [\theta_{Ma}(1, n), \theta_{Ma}(2, n), \ldots \theta_{Ma}(7, n)]$. 
The instantaneous efficiency index for the bilateral movement training is defined as

$$IEI_{bi}(s,n) = W(\theta_{Sl}) \frac{\exp \left( -\sum_{i=1}^{7} (\theta_{Ma}(i,n) - \theta_{Sl}(i,n))^2 \right)}{1 + \sum_{i=1}^{4} \left( \frac{\theta_{Sl}(i,n) - \theta_{ref}(i,n,\phi)_{est}}{\Delta\theta_{Sl}(i)} \right)^2}$$  \hspace{1cm} (6.7)$$

$$EI_{bi}(s) = \frac{1}{N} \sum_{n=0}^{N-1} IEI_{bi}(s,n)$$  \hspace{1cm} (6.8)$$

where $\Delta\theta_{Sl}(i) = \max(\Delta\theta_{Sl}(i)) - \min(\Delta\theta_{Sl}(i))$ means the range of the $i$th joint in the slave side and $\theta_{ref}(i,n,\phi)_{est}$ is the desired reference joint angles for $i$th joint computed for the given end-effector position and the desired swivel angle $\phi_{est}$ estimated by Eq. 3.28 in Section 3.1. Note that the repetition variable $r$ is omitted from $EI_{bi}(s)$ for simplicity. In practice, $EI_{bi}(s,r)$ is computed for each repetition cycle.

The numerator of Eq. 6.7 has a Gaussian distribution such that it is maximized when both $\theta_{Ma}(i)$ and $\theta_{Sl}(i)$ are same. Since the slave side of the robot arm generates smaller torque compared to the master side of the arm, patients should be actively engaged with the robot to make the symmetric arm movement. Thus the numerator indicates how much both hands move symmetrically. The denominator has a minimum value one when the $\theta_{Sl}(i)$ is same as the desired joint angle $\theta_{ref}(i,\phi)_{est}$ and it indicates whether patients are actively engaged with the given tasks at the slave side or not. Note that since all the tasks given to the patients are in the form of reaching task, the desired joint angles for the patient’s natural arm movement will be close to $\theta_{ref}(i,\phi)_{est}$ estimated by Eq. 3.28. By looking at the denominator, one can capture whether patient avoids the natural arm posture like the healthy subjects or not. If patients do not try to move both arms symmetrically and overcome the limited joint range, the efficiency of the therapy will be reduced. It is worth monitoring the efficiency index because the travel distance does not tell us if patients are using their affected arm in a constructive way.
The window function \( W(\theta_{Sl}) \) defined in Eq. 6.9 is a modified sigmoid function where \( W(\theta_{Sl}) \) approaches zero when \( \sum_{i=1}^{7} |\dot{\theta}(i,n)| \leq \theta_{th} \) and approaches one when \( \sum_{i=1}^{7} |\dot{\theta}(i,n)| \geq \theta_{th} \). In this research, sigmoid function is adopted because of its smooth transition around the threshold \( \theta_{th} \) in a closed form. This function can be replaced with other window functions such as signum or simple form of linear functions. By applying this window function to \( IEI_{bi}(s,n) \), only the meaningful joint movement is considered for the data analysis.

\[
W(\theta_{Sl}) = \frac{1}{1 + \exp \left( -\frac{\left( \sum_{i=1}^{7} |\dot{\theta}(i,n)| \right)^2 - \theta_{th}}{h} \right)} \tag{6.9}
\]

Note that there is no optimum value for \( \theta_{th} \) and we have empirically chosen \( \theta_{th} = 1 \) and \( h = 0.5 \) considering the noise signal power of the data.

**Efficiency Index for the Unilateral movement training**

In case of unilateral movement training, the equation should be changed considering that there is no master side. From the previous work in [62, 61], it is shown that the desired joint angles at any time moment is known for the simple reaching and grasping task, the joint angle from the master side \( \theta_{Ma}(i,n) \) can be replaced with desired joint angle \( \theta_{D}(i, \phi_{est}, n) \) based on the swivel angle estimation proposed in Eq. 3.26. The modified instantaneous efficiency for the unilateral movement training is given as

\[
IEI_{uni}(s,n) = W(\theta_{Sl}) \frac{\exp \left( -\sum_{i=1}^{4} \left( \frac{\theta_{D}(i, \phi_{est}, n) - \theta_{Sl}(i, n)}{\Delta \theta_{Sl}(i, n)} \right)^2 \right)}{1 + \sum_{i=1}^{4} \left( \frac{\theta_{Sl}(i, n) - \theta_{ref}(i, n, \phi_{est})}{\Delta \theta_{Sl}(i, n)} \right)^2} \tag{6.10}
\]

\[
EI_{uni}(s) = \frac{1}{N} \sum_{n=0}^{N-1} IEI_{uni}(s,n) \tag{6.11}
\]

Similarly from the other metric introduced in the previous section, the averaged efficiency index \( EI_{bi}(s) \) and \( EI_{uni}(s) \) will be used to represent the result for each session.
6.5.2 Results and Analysis

In this section, we introduce data analysis result based on the evaluation metrics and experimental protocol. The evaluation metric of each game is averaged over the time and repetition for each session to get a scalar value and by collecting the scalar value from all 12 sessions, 12 dimensional vector representing the patient’s progress can be formed. Once the 12 dimensional vectors are extracted from the individual subject and game, they will be averaged over all subjects belonging to the same training group and all applicable games to the specific metric to extract the group level evaluation result. Finally the first order polynomial curve fitting is applied to the 12 dimensional vector. Then conceptually the relative improvement for each training group in terms of the specific metric will be defined as

\[ I = \frac{X_P(12) - X_P(1)}{X_P(1)} \times 100 \]  

where \( X_P(i) \) mean the first order polynomial curve fitting output of 12 dimensional vector from either unilateral or bilateral movement training group. Fig.6.12 shows the exemplary processing result for the range of motion and painted area from a single subject. The range of motion and the painted area from all 12 sessions are plotted as a blue line. The first order polynomial curve fitting result is plotted as a black dotted line. Then the relative improvement to the initial session result can be achieved by Eq. 6.12.

6.5.3 Range of Motion

The ranges of each joint were measured from seven different movements which are shoulder abduction-adduction, shoulder flexion-extension, shouder rotation, elbow flexion-extension,
Figure 6.13: a) The range of motion improvement in percent. The X axis in this figure means shoulder abduction-adduction, shoulder flexion-extension, shouder rotation, elbow flexion-extension, wrist pronation-supination, wrist flexion and wrist radial-ulnar. b) Percentage painted area improvement.

wrist pronation-supination, wrist flexion and wrist radial-ulnar. The Fig. 6.13 shows the percentage joint range improvement $I_{joint}(i)$ at $i$th joint from unilateral and bilateral training group.

Let $\Delta \theta_i^j(S,k)$ and $\Delta \theta_i^j(1,k)$ mean the $i$th joint angle range of subject $k$ measured at the final and initial session after the first order polynomial fitting is applied to the 12 session range of motion plot. Then $I_{joint}(i)$ for either unilateral or bilateral training group is defined as

$$I_{joint}(i) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{\Delta \theta_i^j(S,k) - \Delta \theta_i^j(1,k)}{\max \Delta \theta_i^j(k)} \right) \times 100$$ (6.13)

where $\max \Delta \theta_i^j$ is the maximum joint angle range of $i$th joint. Note that two patient did not finish the scheduled 12 sessions due to their personal schedule issue. Thus $S$ will be 12 except two patients. This will be applied to other metrics in the same way. The result shows that the unilateral movement training group has relatively higher improvement for the proximal extremities while the bilateral movement training shows higher improvements for distal extremities. In general, it is known that the improving wrist joints are more difficult than improving the
Figure 6.14: Travel Distance: a) percentage travel distance improvement for four different games and b) averaged travel distance for four different games. The Y axis in b) is meter in unit.

shoulder joints movement. From this aspect, bilateral movement training can be an efficient rehabilitation scheme proper for the distal extremities.

6.5.4 Painted Area

The painted area is only for the paint game. Fig. 6.13(b) shows that the bilateral movement training group has a higher percentage painted area improvement, which is about 23% while the unilateral group patients showed 8% improvement. The relative improvements
for painted area $I_{PA}$ is computed based on Eq.6.14.

$$I_{PA} = \frac{1}{5} \sum_{k=1}^{S} \left( \frac{PA(S,k) - PA(1,k)}{PA(1,k)} \right) \times 100$$ (6.14)

where $PA(S,k)$ and $PA(1,k)$ mean the painted area of bilateral or unilateral group subject $k$ at the final and initial session. Note that the first order polynomial fitting is omitted for this metric since there is no fluctuation in data.

### 6.5.5 Travel Distance

Travel distance is estimated for flower (assisted, unassisted), paint and reach games. Relative improvement to the initial travel distance for each game is computed by Eq. 6.15 and the evaluation result is shown in Fig. 6.14. By looking at the percent improvement of travel distance, it is hard to decide which rehabilitation scheme is better. The averaged travel distance is computed by Eq. 6.16 and shown in Fig. 6.14(b). According to this, bilateral training group patients showed higher travel distance for most games. This is possible due to the fact that bilateral group patients needed some adaptation time to be used to the coupled motor control scheme. Especially for the assisted flower game[Fig. 6.14(b)], gap between the bilateral and unilateral training group is biggest. This is possible because the patients in unilateral training group were directly taught by the robot to make the impaired arm move along the desired path even throughout sessions.
\[ I_{TD}(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{TD_e(S,g,k) - TD_e(1,g,k)}{TD_e(1,g,k)} \right) \times 100 \quad (6.15) \]

\[ I_{eTD}(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{1}{5} \sum_{s=1}^{5} TD_e(s,g,k) \right) \quad (6.16) \]

where \( g \in \{Assisted\ flower, Unassisted\ flower, paint, reach\} \)

6.5.6 Area around straight line

AR (Area-around-straight-line) is defined for the flower game (unassisted and assisted). Similarly from the above metrics, the data analysis for AR is defined by Eq. 6.17 and Eq. 6.18.

\[ I_{AR}(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{AR_e(S,g,k) - AR_e(1,g,k)}{AR_e(1,g,k)} \right) \times 100 \quad (6.17) \]

\[ I_{eAR}(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{1}{5} \sum_{s=1}^{5} AR_e(s,g,k) \right) \quad (6.18) \]

where Eq. 6.17 and Eq. 6.18 show the relative improvement and the averaged AR defined for each game. Eq. 6.17 follows the same notational convention as Eq. 6.19. In this case, the unilateral movement training group patients showed better result. This is due to the fact that the AR metric is closely related to the path planning of the arm motion. The unilateral training group patients are taught to follow the optimum path by the robot during the whole sessions. On the other hand, bilateral training group used their own path planning scheme. Therefore
Figure 6.15: AR(Approximated area computation around straight line): a) AR improvement in percent for flower(assisted and unassisted) games and b) An averaged AR for flower(assisted and unassisted) games. The Y axis in b) is $m^2$ (meter squared) in unit.

bilateral group patient’s arm movement formed a larger AR. The AR metric might be useful to see the improvement of the patient’s path planning skill.

### 6.5.7 Efficiency Index

Since the efficiency index can be extracted from flower(Assisted and Unassisted flower game), paint and reach game, the relative improvement representing either unilateral or bilateral training group will be based on Eq. 6.19.

\[
I_EI(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{EI_{uni,b}(S,g,k) - EI_{uni,b}(1,g,k)}{EI_{uni,b}(1,g,k)} \right) \times 100
\]

(6.19)

\[
I_eEI(g) = \frac{1}{5} \sum_{k=1}^{5} \left( \frac{1}{S} \sum_{s=1}^{S} EI_{uni,b}(s,g,k) \right)
\]

(6.20)

where $EI_{uni,b}(s,g,k)$ is the extended version of $EI_{b}(s)$ in Eq. 6.8 which is also estimated for the specific game type $g$ and subject $k$. This type of notation extension will be applied to the
Figure 6.16: Efficiency Index Improvement: a) Percentage efficiency index improvement for four different games and b) An averaged efficiency index (over the entire session) for four different games

other metrics in the following sections. Fig. 6.16(a) shows the comparison result of $I_{EI}(g)$ from the bilateral and unilateral movement training group. In addition, the averaged $I_{EI}(g)$ over all subject and sessions are estimated by Eq. 6.20 and plotted in Fig. 6.16(b). From the result in Fig. 6.16(a), we know that the bilateral movement training delivered a better rehabilitation result to the patients for most games except the reach game where both patient group showed negative improvement. It implies that patients in bilateral movement training group tried to make more natural human arm posture as the therapy continues. Also the result in Fig. 6.16(b) showed that the bilateral movement training group showed more natural human arm movement pattern.
throughout the entire session and games.

Table 6.4: Fugl-Meyer Score test result (Bilateral training group)

<table>
<thead>
<tr>
<th></th>
<th>Bilateral training group</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S10</td>
<td>S6</td>
<td>S5</td>
<td>S11</td>
<td>S15</td>
</tr>
<tr>
<td>Affected side</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>L</td>
<td>R</td>
</tr>
<tr>
<td>Hand dominance</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
</tr>
<tr>
<td>Function level</td>
<td>H</td>
<td>H</td>
<td>L</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>Fugl Meyer(Pre)</td>
<td>28</td>
<td>29</td>
<td>16</td>
<td>23</td>
<td>26</td>
</tr>
<tr>
<td>Mean±Std(Pre)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fugl Meyer(Post)</td>
<td>31</td>
<td>33</td>
<td>21</td>
<td>27</td>
<td>29</td>
</tr>
<tr>
<td>Mean±Std(Post)</td>
<td>28.2±4.6</td>
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<tr>
<td>Difference(%)</td>
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<td>13.8</td>
<td>31.3</td>
<td>17.4</td>
<td>11.5</td>
</tr>
<tr>
<td>Mean±Std(Diff)</td>
<td>16.9±8.4</td>
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</tr>
</tbody>
</table>

R and L mean Right hand and Left hand individually.
H, L and M mean High, Low and Moderate individually.

Table 6.5: Fugl-Meyer Score test result (Unilateral training group)

<table>
<thead>
<tr>
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<th>Unilateral training group</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S2</td>
<td>S1</td>
<td>S3</td>
<td>S8</td>
<td>S13</td>
</tr>
<tr>
<td>Affected side</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>Hand dominance</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>L</td>
<td>R</td>
</tr>
<tr>
<td>Function level</td>
<td>L</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>M</td>
</tr>
<tr>
<td>Fugl Meyer(Pre)</td>
<td>19</td>
<td>36</td>
<td>18</td>
<td>19</td>
<td>27</td>
</tr>
<tr>
<td>Mean±Std(Pre)</td>
<td>23.8±7.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fugl Meyer(Post)</td>
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<td>41</td>
<td>21</td>
<td>24</td>
<td>29</td>
</tr>
<tr>
<td>Mean±Std(Post)</td>
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</tr>
<tr>
<td>Difference(%)</td>
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<td>13.9</td>
<td>16.7</td>
<td>26.3</td>
<td>7.4</td>
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<tr>
<td>Mean±Std(Diff)</td>
<td>18.1±8.2</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R and L mean Right hand and Left hand individually.
H, L and M mean High, Low and Moderate individually.

6.5.8 Fugl-Meyer score

We also included Fugl-Meyer score test result to see if there is correspondence with other evaluation metrics. The test was done twice by the therapist before the therapy begins.
and after the whole 12 sessions therapy was finished. In addition to the bilateral and unilat-
eral training group, another patient group treated by physical therapist also participated in the
Fugl-Meyer score test and all the results are summarized in Table. 6.4, 6.5 and 6.6. All patients
group showed significant improvement in terms of the percent difference result in Table. 6.4, 6.5
and 6.6. On average most improvement was in the Physical Therapy Group group. the physi-
cal therapist group showed the highest improvement(16.94%), followed by unilateral and then
bilateral training group. There are many reasons for why this could have happened because the
physical therapist . group got exercises for large gross motor tasks (shoulder, elbow movements)
as well as fine motor which includes the wrist and fingers. However for the low and moderate
function group, bilateral movement training group showed the highest improvement(31.3% for
low function patient and 17.4% for the moderate function patient.) compared to the other two
training group. Since there is not enough number of subjects to extract the statistically mean-
ingful information, it is too early to address a specific training scheme is superior to others.
6.6 Result and Conclusion

So far we have introduced the robot-aided stroke rehabilitation system and its clinical trial based on the bilateral and the unilateral movement training schemes. The patient's rehabilitation results were evaluated individually for all patients based on the five different assessment metrics including one new metric, which is efficiency index. Although only 10 patients participated in the rehabilitation therapy for short 12 sessions, the meaningful result could be achieved. Result showed that the bilateral movement training scheme delivered better rehabilitation result with respect to the wrist joint movement, painted area and efficiency index while the unilateral movement training showed relatively higher improvements for the travel distance and area-around-straight line. Unlike the unilateral training group who were forced not to move the wrist joints by the force field from the robot, bilateral training group could consistently move the impaired wrist joint by borrowing the assistive force from the healthy arm such that this group of patients achieved more functionality on the wrist joint. Efficiency index also shows that bilateral group patients showed improvement from an aspect of the natural human arm movement for the unconstrained reaching tasks. On the other hand travel distance and area-around-straight line are assessment metrics about the efficient path-planning. Since the unilateral movement training group are taught the optimum path by the assisting force from the robot, they outperformed bilateral training group in travel distance and AR. It implies that for more improved rehabilitation effect, both movement training schemes needs to be consolidated together. Finally, the most well known and widely used Fugl-Meyer score was tested for three patient groups and the result showed that all therapy group showed the significant improvement.
Bibliography


[38] Tomohiro Hayashi, Hiroaki Kawamoto, and Yoshiyuki Sankai. Control method of robot suit hal working as operator's muscle using biological and dynamical information. In


[103] Byblow WD Stinear JW. Rhythmic bilateral movement training modulates corticomotor


[110] Xuguang Wang. A behavior-based inverse kinematics algorithm to predict arm pre-
hension posture for computer-aided ergonomic evaluation. *Journal of Biomechanics*,

[111] Eric T. Wolbrecht, Vicky Chan, Vu Le, Steven C. Cramer, David J. Reinkensmeyer, and
James E. Bobrow. Real-time computer modeling of weakness following stroke optimizes
robotic assistance for movement therapy. In *Proceedings of the 3rd International IEEE

Bobrow, and D. J. Reinkensmeyer. A pneumatic robot for re-training arm movement
after stroke: Rationale and mechanical design. In *Proceedings of the 2005 IEEE 9th
International Conference on Rehabilitation Robotics*, IL, USA, July 2005.

product-of-exponentials formula. Master’s thesis, Nanyang Technological University,
2000.

[114] Feng Yang and Xiugan Yuan. An inverse kinematical algorithm for human arm move-
ment with comfort level taken into account. In *IEEE Conference on Control Applications*,

[115] Leslie Ying, Dan Xu, and Zhi-Pei Liang. On tikhonov regularization for image recon-
struction in parallel mri. In *Proceedings of the 26th Annual International Conference of

