Mechatronic Considerations of Assistive Systems for Gait Rehabilitation

by

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Professor J. Karl Hedrick
Professor Claire Tomlin

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Mechatronic Considerations of Assistive Systems for Gait Rehabilitation

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Abstract

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Professor Masayoshi Tomizuka, Chair

As the number of patients requiring gait rehabilitation treatments is increasing, assistive systems for gait rehabilitation are being actively investigated. Assistive systems enable more efficient rehabilitation by providing objective values for indicating the patient’s status and assistive torque for practicing normal trajectories for rehabilitation. This thesis investigates several mechatronic technologies of assistive systems for gait rehabilitation, including (1) estimation and evaluation of the patient’s status, (2) monitoring systems, (3) control of assistive systems, and (4) implementation of rehabilitation algorithms.

Estimation and evaluation of a patient’s status based on pertinent measurements is the first step toward determining appropriate rehabilitation intervention methods. This thesis introduces an algorithm that estimates gait phases using a hidden Markov model (HMM) based on ground reaction forces (GRFs) measured by force sensors embedded in shoes, called Smart Shoes. The GRFs and the center of the GRFs (CoGRF) are used for observing the patient’s status, and gait abnormality is calculated based on deviations from healthy GRF levels. This information is supplied to the monitoring system, which is implemented as a mobile system and a tele-system using the Internet. Assistive torque is required for seriously impaired patients to achieve the desired motion or practice normal trajectories. Ideal force mode control is necessary for natural interactions between the assistive system and the patient. In this thesis, robust control algorithms for precise and safe generation of the desired torque are discussed. The proposed algorithms have been applied to the previously developed assistive systems such as a rotary series elastic actuator (RSEA), a compact rotary series elastic actuator (cRSEA), and a cable-driven assistive system. As a decision-making process for rehabilitation, both a power augmentation method and a rehabilitation method are discussed. For the power augmentation method, the joint torque of the lower extremities is estimated using a human model with seven links and four different ground contact conditions. For gait rehabilitation, a potential field around the desired trajectory and an iterative learning algorithm inspired by repetitive gait motions are proposed for determining the desired assistive torque. The proposed methods have been verified experimentally, including clinical tests using actual patients.
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Chapter 1

Introduction

1.1 Assistive Systems for Gait Rehabilitation: Necessity or Fashion?

As the number of elderly people increases [18,24,25], there is a growing demand for rehabilitation services. In the United States, approximately 40 million people are currently over the age of 65, and this number is expected to be doubled to approximately 85 million by 2050, as shown in Fig. 1.1. Dramatic changes in demographic structures are also taking place in other countries, as shown in Fig. 1.2. For example, the percentage of the Japanese population over the age of 65 is projected to increase to 30% by 2025 and to 36% by 2050 [24]. With continually increasing life expectancies and an aging population, the number of incidences of age-related pathologies involving gait disorders, such as strokes and Parkinson’s Disease, is increasing.

A stroke is the major cause of permanent disability in the United States. Approximately 795,000 people suffer a stroke each year in the United States, and more than 4 million people have survived a stroke or a brain attack and are living with the after-effects [26, 90]. The fact that nearly three-quarters of all strokes occur in people over the age of 65 and that the risk of having a stroke more than doubles each decade after the age of 55 explains the increased number of stroke patients in an aging society [26, 90]. Parkinson’s Disease (PD) is one of the most common neurological disorders; 500,000~1.5 million people are estimated to be affected by PD in the United States. PD typically occurs between 40 and 70 years of age, with peaks in the sixth decade of life [41].

In addition to age-related pathologies, the number of patients suffering from gait disorders caused by cerebral palsy (CP), multiple sclerosis (MS), or spinal cord injury (SCI) is increasing. CP affects body movement and muscle coordination, and 2.8 out of every 1,000 children born each year in the United States are afflicted at birth. Approximately 5,000 infants and toddlers, as well as 1,200~1,500 preschoolers, are also diagnosed with CP each year in the United States [39]. MS is a chronic disease of the central nervous system and is the third-leading cause of disabilities in young adults in the United States, where the total number of MS patients is estimated to be approximately
Figure 1.1: Changes in the age distribution of people 65 and older in the U.S. population over the last century and projected through 2050 [35].

350,000 [112]. SCI is the leading cause of disabilities in young adults in the United States. The number of incidences of SCI in the United States has been estimated to be between 30 and 60 per million per year [89].

Walking ability, an important ability for quality of life and participation in social and economic activities, can be affected by these aforementioned neurological disorders. The exact mechanism used for walking is still not clear; however, breakthroughs in neuroscience have revealed that humans with gait disorders can increase their motor capabilities by practicing repetitive walking patterns [19, 36]. Currently, this type of therapy is conducted with the aid of two or more physical therapists who manually move the patient’s legs in a walking pattern. However, the manual form of this type of therapy is strenuous for therapists and is labor and cost intensive.

Owing to an increased demand for gait rehabilitation and the drawbacks of manual rehabilitation therapy, improved rehabilitation systems are required for more effective gait rehabilitation. To address this requirement, robot technologies have been applied to gait rehabilitation therapy. With robot-assisted gait rehabilitation, more accurate and repetitive exercises can be achieved over longer periods of time. Active research on gait rehabilitation systems can be seen through the number of academic papers being written on the subject. The approximate number of articles submitted to the International Conference on Rehabilitation Robotics (ICORR) from 1997 to 2007 shows a sharp increase in articles on rehabilitation robotics, rising from 33% to almost 80% of the submitted articles [68]. This research on gait rehabilitation systems is not a temporary fashion, it is a necessity of our modern age.
Figure 1.2: Changes in demographic structures of US, China and Japan [18, 24].
1.2 System Diagrams with Human Motor Control System

Movement is made in response to a variety of signals from the external or internal environment. Figure 1.3 shows the orchestrated activity of many brain centers, muscles, and the nervous system in the human motor control system to achieve the desired movement. The higher center in the cerebral cortex makes a plan of action based on the sensory information in relation to the goal. The parietal (one of nonmotor cortical areas) and premotor areas, along with other parts of the nervous system, are involved in identifying targets in space, choosing a course of action, and programming movements. The plan is sent to the motor cortex, and the muscle groups are specified. The plan is also sent to the cerebellum and basal ganglia, which modify it to refine the movement. The cerebellum sends an update of the movement output plan to the motor cortex and the brainstem. Descending pathways from the motor cortex and the brain stem then activate spinal cord networks, spinal motor neurons activate the muscles, and motion is achieved. The difference between a generated motion and reference motion serves as feedback for the performance. If a difference exists between the feedback received and the reference, then an error is signaled and a correction is applied.

For the control of walking motions, it is known that central pattern generators in the spinal cord play an important role in generating basic walking patterns by making rhythmic contractions of required muscles [103]. However, the closed-loop control system shown in Fig. 1.3 is still useful to
explain how the walking motions controlled against external environment and can be rehabilitated thorough gait rehabilitation therapy since the walking patterns are affected by sensory feedback including perception and memory [103]. In other words, although the central pattern generators are able to produce stereotyped locomotor patterns and perform certain adaptive functions, descending pathways from higher centers and sensory feedback from the periphery allow the rich variation in locomotor patterns and adaptability to task and environmental conditions [109]. Moreover, the closed-loop control system is usually important in the situation that requires the system to “control itself” for long periods of time. Because rehabilitation is a slow process and relies more on feedback from the patient, the closed-loop model in Fig. 1.3 is used for representing the human motor control system in this thesis.

The closed-loop human motor control system in Fig. 1.3 can be simplified by representing the brain and spinal cord as a controller, muscles as an actuator, and the human body as a plant to be controlled. Then, the block diagram of the human motor control system interacting with the assistive systems can be drawn as in Fig. 1.4. The non-gray parts in the figure stand for the simplified human motor control system. Assistive systems for gait rehabilitation imitate the functions of physical therapists by providing audio/video and/or force feedback to patients. For lightly impaired patients who can move their body easily, monitoring systems that provide audio/video feedback on the patient’s status may be sufficient to help them rehabilitate on their own. As shown in [Monitoring system] in Fig. 1.4, a monitoring system provides augmented signals using ground reaction forces or joint angles enabling the patient to recognize his/her status.

Monitoring may not be sufficient for seriously impaired patients who cannot move their bodies easily. Such patients need assistive torque to achieve normal motion or exercise their motion tra-
jectors for rehabilitation. An active rehabilitation system applies an assistive joint torque, $\tau_A$, to augment the patient’s own joint torque, $\tau_H$. The concept of an active rehabilitation system is shown in [Active rehabilitation system] in Fig. 1.4. Control of the active rehabilitation system is divided into two parts: a rehabilitation algorithm and a motion controller of the actuator. The rehabilitation algorithm determines the desired assistive torque, $\tau_{Ad}$, based on an appropriate rehabilitation strategy, which may depend on the physical therapist’s personal experience and extensive information regarding the patient’s status. The objective of the motion controller is to let the actuator generate the desired assistive torque precisely. In this thesis, mechatronic technologies for the monitoring system and the active rehabilitation system including the motion controller and the rehabilitation algorithm, are discussed.

1.3 State of the Art

In recent years, there have been many attempts to develop assistive systems for power augmentation or rehabilitation. In this chapter, previous research related with assistive systems for gait rehabilitation such as power augmentation systems, robotic gait rehabilitation systems, actuator modules using active or passive elements, and monitoring systems are introduced.

Power augmentation systems have been developed for soldiers, fire fighters, and other emergency personnel to help carry heavy loads such as food, rescue equipment, first-aid supplies, and weaponry. The Hybrid Assistive Limb (HAL), shown in Fig. 1.5(a), is a cyborg-type robot that can expand and improve the wearer’s physical capabilities. In this system, electrical motors are used as the main power sources, and biological signals are measured to determine the user’s intention and control the robot suit [34, 48]. The Berkeley Lower Extremity EXoskeleton (BLEEX), shown in Fig. 1.5(b), was developed for military purposes. It utilizes a hydraulic actuator, and a positive control feedback loop is used to increase the sensitivity of a human body, i.e., the user can perform the same task with less muscular power [56, 124]. Since such technologies applied for power augmentation systems can be converted to assistive systems for rehabilitation, the power augmentation systems are noteworthy for rehabilitation systems. HAL has already been applied to help assist in the walking motion of wearers with walking difficulties or weakened muscles, as shown in Fig. 1.5(c).

Assistive systems for gait rehabilitation are usually developed for use with a treadmill or a body-weight support system. The Driven Gait Orthosis (DGO), shown in Fig. 1.6(a), can be used to move the legs of a patient in a physiological manner on a moving treadmill. Actuators at the knee and hip joints are controlled using a position controller [30]. The Mechanized Gait Trainer (MGT), shown in Fig. 1.6(b), provides a gait-like movement that simulates the stance and swing phases with an actual lifting of the foot during the swing phase using two footplates [49]. The low backward movement of the footplates simulates the stance phase while the forward movement simulates the swing phase. The Haptic Walker, shown in Fig. 1.6(c), offers a haptic locomotion interface using two programmable foot platforms with permanent foot machine contact, which provides up to six plus one degrees of freedom (DOF) per foot [106]. It is equipped with electrical
direct drive motors, enabling highly dynamic footplate motions, and six DOF force/torque sensors are mounted under each foot platform for contact force measurements. The LOwer extremity Powered ExoSkeleton (LOPES), shown in Fig. 1.6(d), combines a freely translatable and 2D-actuated pelvis segment with a leg exoskeleton containing three actuated rotational joints—two at the hip and one at the knee. The joints are impedance controlled to allow bidirectional mechanical interaction between the robot and the training subject [118]. Figure 1.6(e) shows the Gravity Balancing leg Orthosis (GBO), which was designed to assist persons with hemiparesis to walk through the elimination of gravity effects. This system can fully or partially gravity balance a human leg over its range of motion, and it can be tunable to the geometry and inertia of a specific human subject to achieve the desired level of gravity balancing [17]. The Active Leg EXoskeleton (ALEX), shown in Fig. 1.6(f), has a force-field controller that can apply suitable force to the leg and help it move in a desired trajectory. The interaction forces between the subject and orthosis are designed to be “assist-as-needed” for safe and effective gait training [17].

Several gait rehabilitation systems have been commercialized and are available in the market. Tibion, shown in Fig. 1.7(a), is a robotic knee that helps patients with weakness in their quadriceps to extend their legs. The device has shown promise in improving the mobility of stroke patients [115]. Re-Walk, shown in Fig. 1.7(b), was developed for wheelchair users with lower-limb disabilities to help them stand, walk, and even climb stairs [72]. It consists of a light wearable brace support suit that integrates actuation motors at the joints, an array of motion sensors, a computer control system, and safety algorithms. Lokomat, shown in Fig. 1.7(c), is an automated gait orthosis for use on a treadmill and has been in the market since 2001 [51]. It has been recently equipped with an augmented feedback system and a touch screen for better feedback to the patient.

Actuator modules for assistive systems have also been actively studied. The Series Elastic
Figure 1.6: Robotic gait rehabilitation systems.
CHAPTER 1. INTRODUCTION

Figure 1.7: Commercialized gait rehabilitation systems.

(a) Tibion \[115\]  
(b) Re-Walk \[72\]  
(c) Lokomat \[51\]

Figure 1.8: Gait rehabilitation systems with active elements.

(a) SEA \[92, 97, 98, 102\]  
(b) AAFO \[22\]  
(c) Pneumatic muscle \[46\]

Actuators (SEA), shown in Fig. 1.8(a), utilize a compliant element, a linear spring, between the motor and actuator output to intentionally reduce the stiffness of the actuator. A position sensor measures the deflection, and the force output is accurately controlled \[92, 97, 98, 102\]. The Active Ankle Foot Orthosis (AAFO), shown in Fig. 1.8(b), was designed to treat foot drop by utilizing the SEA \[22\]. In addition to electric motors, a pneumatic system is applied to the actuator module. Figure 1.8(c) shows an ankle foot orthosis that provides plantar flexion assistance while walking. It is actuated using artificial pneumatic muscles that consist of an expandable internal bladder surrounded by a braided shell. When the internal bladder is pressurized, it expands in a balloon-like manner. The braided shell constrains the expansion \[46\].

In addition to active elements such as electric motors or pneumatic actuators, passive elements are also applied to gait rehabilitation systems. Figure 1.9(a) shows the Active Knee Rehabilitation
Orthotic Device (AKROD) for gait retraining in stroke patients. In this system, a variable damper component is used to facilitate knee flexion while standing by providing resistance to knee buckling. The variable damper component is obtained through an electro-rheological fluid element that connects to the output of the gear system [87]. Figure 1.9(b) shows a rehabilitation device used to strengthen different muscle groups based on the torque-generating capability of muscle, which changes with the joint angle. In this system, a damper with smart magneto-rheological fluids provides passive exercise force. An adaptive control regulates exercise force precisely following the muscle strengthening profile prescribed by a physical therapist [37].

Monitoring systems that provide augmented information to a patient or physical therapist have also been actively investigated. These monitoring systems are usually used in conjunction with an active rehabilitation system. In such monitoring systems, electromyographic (EMG) recordings [32, 82], kinematic quantities [29, 50], and kinetic measures are processed and displayed visually or acoustically [20, 38, 73, 81, 101]. Figure 1.10 shows the visual feedback program interface used in Lokomat [73].

1.4 Thesis Overview

To address the requirements of assistive systems for gait rehabilitation, several mechatronic technologies for gait rehabilitation systems are designed in this thesis. This thesis is organized as follows.

[Chapter 2: Gait Phase Analysis based on Ground Reaction Forces]
This chapter introduces an algorithm that estimates gait phases based on ground reaction forces (GRFs) measured force sensors embedded in shoes, called Smart Shoe. A hidden Markov model (HMM) is used for estimating the gait phases, while GRFs are used as observations. The estimated
gait phases are utilized for indicating the patient’s status as well as for controlling the assistive systems for rehabilitation.

[Chapter 3: Monitoring Systems for Gait Rehabilitation]
In this chapter, monitoring systems that provide visual feedback information to patients and physical therapists are discussed. A mobile monitoring system was developed as a hand-held device equipped with a touch screen. It provides GRFs and center of ground reaction forces (CoGRF) in real time, and the patient can practice his/her normal gait pattern using provided visual feedback. Moreover, the degree of gait abnormality is calculated based on deviations from the normal GRF bands. A tele-monitoring system utilizing an inertial measurement unit (IMU) and the Internet is also discussed in this chapter.

[Chapter 4: Control of Assistive Systems for Rehabilitation]
Ideal force mode control is required for natural interactions between the assistive system and the patient, which means low mechanical impedance and back drivability of the actuator. However, nonlinear friction, backlash, and modeling uncertainties make precise torque control challenging. This chapter discusses robust control algorithms for precise and safe generation of the desired assistive torque. The developed control algorithms have been applied to previously developed assistive systems such as a rotary series elastic actuator (RSEA) and a compact rotary series elastic actuator (cRSEA).

Using the introduced assistive systems and control algorithms, the mechanical impedance of the actuator is reduced, but the mass of the actuator is a still large burden to users. To separate the actuator from the user’s body, a cable-driven assistive system was previously proposed. The cable tension controller to compensate for the cable friction and maintain cable tension is discussed in this chapter.
CHAPTER 1. INTRODUCTION

[Chapter 5: Implementation of Rehabilitation Algorithms]

The decision-making process for gait rehabilitation, i.e., how the assistive torque should be applied in terms of magnitude and timing, is studied in this chapter. Both a power augmentation method and a rehabilitation method are discussed according to the level of the patient’s impairment. If the patient’s muscular function is permanently damaged, the power augmentation algorithm is applied based on the estimated joint torque. For the estimation of the joint torque, a human body model with seven links and four different ground contact conditions is used.

For rehabilitation of the muscular or nervous systems, repetitive practice for normal motion trajectories is required. The assistive system applies appropriate assistive torque to the patient’s joint if it deviates from the desired trajectory, allowing the patient to recognize and practice the normal trajectory. A potential field around the desired trajectory and an iterative learning algorithm inspired by repetitive gait motions are proposed to determine the desired assistive torque.

[Chapter 6: Concluding Remarks and Open Issues]

Concluding remarks of this thesis are drawn and the remaining open issues are discussed as future work.
Chapter 2

Gait Phase Analysis based on Ground Reaction Forces

2.1 Introduction

For effective gait rehabilitation treatments, the status of a patient’s gait needs to be analyzed precisely. Usually, the status of a patient’s gait is analyzed by physical therapists with visual observations or verbal descriptions. Since these qualitative diagnostic methods depend on physical therapists’ experience and knowledge, more objective methods to analyze patients’ gaits are required.

Since the gait motions are cyclic with several gait phases, the gait motions can be analyzed by the gait phases [96]. The gait phases are observed by various gait data such as foot pressure distributions and joint angles. Due to the easiness and the practicality of measuring foot pressure distributions, shoe-type sensors have been devised by previous researchers, and several methods for the detection of gait phases have been suggested. Morris et al. developed a shoe-integrated sensor system for wireless gait analysis and real-time feedback [83]. Bamberg et al. developed a shoe-integrated wireless sensor system by applying four force sensitive resistors (FSRs) and a bend sensor [16]. Papas et al. made a gait phase detection system with three FSRs and a gyroscope [94]. These research, however, detected the gait phases as discrete events, which is not correct in actual gait motions.

In the previous work, a fuzzy logic was applied for the continuous detection of gait phases with the ground reaction forces (GRFs) measured by Smart Shoes [62, 67]. Smart Shoes were developed to measure GRF by embedded air-bladder type force sensors under the insole. By utilizing the GRF patterns in the fuzzy logic, the gait phases are detected continuously and smoothly [62, 67]. The fuzzy logic method uses a fuzzy membership function with appropriate threshold values and fuzzy rule bases. Due to the use of a fuzzy membership function and fuzzy rule bases, the fuzzy logic method can be considered as a pattern-based gait phase detection method. The fuzzy logic method detects the gait phases quite well, but it fails to detect the gait phases correctly for some of abnor-
normal gait data from patients. Since the fuzzy logic uses threshold values with fuzzy membership functions, if the ground reaction force (GRF) pattern of the abnormal gait is similar to that of the normal gait over the threshold values, then the gait phases are not detected correctly.

In this chapter, a gait phases analysis method based on a hidden Markov model (HMM) is discussed [13, 14]. The proposed gait phase detection method uses the actual GRF values instead of GRF patterns which rely on threshold values, fuzzy membership functions, and fuzzy rule bases. Thus, it can be considered as a value-based gait phase detection method. In the HMM, six gait phases are considered as the hidden states, and they are inferred by the GRF observations measured by Smart Shoes. For the inference of the gait phases, the conditional probability of the observations with a given state is required. To calculate the conditional probability, the GRFs of normal gait are approximated as Gaussian distributions by collecting many GRF data of normal gait, and the GRFs are classified by gait phases. The transition matrix which shows the transition probabilities is used to check the abnormal transition between gait phases. The proposed method is verified by actual gait data.

2.2 Gait Phases and Smart Shoes

2.2.1 Gait Phases

Walking motions are divided into two basic motions, stance and swing, and there are eight gait phases in those basic motions which were suggested by the Rancho Los Amigos gait analysis committee [96]. The stance motions include initial contact, loading response, mid-stance, terminal stance and pre-swing phases, and the swing motions include initial swing, mid-swing and terminal swing. Since the gait motions are cyclic, the gait phases are repeated in each stride. In normal gait, the gait phases appear sequentially from an initial contact phase to a terminal swing phase. In abnormal gait, however, the sequence of gait phases may be different from those of normal gait. Thus, the status of gait can be diagnosed by analyzing the gait phases, and the effectiveness of a rehabilitation treatment can be evaluated by analyzing the gait phases before and after the rehabilitation treatment.

The cyclic gait motions result in repetitive and unique foot pressure patterns, thus the gait phases can be detected by the foot pressure distributions. Figure 2.1 shows the gait phases of normal gait and the expected foot pressure pattern in each gait phase. In the Initial Contact phase (IC), pressure at the heel increases as the heel contacts the ground. The pressure at the forefoot increases in the Loading Response phase (LR) as the forefoot starts to contact the ground. In the Mid-Stance phase (MS), foot pressure is found across the entire foot. In the Terminal Stance phase (TS), there should be no heel pressure measured, since the heel does not touch the ground. In the Pre-Swing phase (PS), there is foot pressure only at the forefoot around the hallucus. Foot pressure is not observed in the Swing phase (SW), since the foot is in the air. These foot pressure patterns appear repetitively and sequentially in normal gait.
2.2.2 Smart Shoes

For the measurement of the foot pressure pattern, a force sensitive resistor (FSR) has been most frequently used [16, 83, 94]. However, the FSR does not adequately reflect the actual foot pressure due to its small area and limited sensing range. Smart Shoes shown in Fig. 2.2 were originally proposed for the detection of gait phases by measuring the ground reaction force (GRF) in feet [3, 62, 67]. The GRFs are measured by a novel force sensor which consists of an air bladder made by winding a silicone tube and an air pressure sensor. Figure 2.3 shows the schematic sketch of the air bladder sensor. When the foot presses the air bladder, it is deformed, and its pressure change is measured by the air pressure sensor. The light weight and easy implementation of the air bladder sensor contribute to the mobility of Smart Shoes. To measure the forces exerted by the foot accurately, a dynamics compensator is applied considering the physical property (i.e., hysteresis) of an air bladder [3, 67]. Considering the foot pressure distribution [74, 111], four air bladder sensors are installed in Smart Shoes at the hallux, the first metatarsophalangeal joint (Meta1 in Fig. 2.2(b)), the fourth metatarsophalangeal joint (Meta4 in Fig. 2.2(b)) and the heel, as shown in Fig. 2.2(b).

The performance of the air bladder sensor in Smart Shoes was verified by a loadcell. A device with a loadcell shown in Fig. 2.4(a) was developed and used to check the performance of the air bladder sensor. The force measured by the air bladder was compared with the reference force which was measured by a loadcell. As shown in Fig. 2.4(b), there are sliding guides to apply the force to the perpendicular direction of the air bladder. Considering the normal walking speed, the force was applied with the bandwidth up to 4 Hz. Note that the applied force and the measured force by the air bladder sensor show linear relationship as shown in Fig. 2.5.
CHAPTER 2. GAIT PHASE ANALYSIS BASED ON GROUND REACTION FORCES

(a) Smart Shoes

(b) Location of air bladder sensors (Meta1/Meta4: first/forth metatarsophalangeal joint)

Figure 2.2: Smart Shoes [67].

---

Figure 2.3: Schematic sketch of air bladder sensor (Each variable used in figure represents: $F =$ the force exerted by a foot, $P =$ the air pressure in an air bladder, $A =$ the cross-sectional area of the air bladder, $c =$ a conversion constant of an air pressure sensor, and $V_o =$ the voltage output of the air pressure sensor) [67].
CHAPTER 2. GAIT PHASE ANALYSIS BASED ON GROUND REACTION FORCES

Figure 2.4: Experimental setup for performance test of the air bladder sensor.

Figure 2.5: Performance of air bladder sensor.
2.3 Gait Phase Analysis based on a Hidden Markov Model (HMM)

For effective gait rehabilitation treatments, the status of a patient’s gait needs to be analyzed precisely. Since the gait motions are cyclic with several gait phases, the gait motions can be analyzed by gait phases. In this chapter, a hidden Markov model (HMM) is applied to analyze the gait phases in the gait motions. Smart Shoes are utilized to obtain the ground reaction forces (GRFs) as observed data in the HMM. The posterior probabilities from the HMM are used to infer the gait phases, and the abnormal transition between gait phases are checked by the transition matrix. The proposed gait phase analysis methods have been applied to actual gait data, and the results show that the proposed methods have the potential of tools for diagnosing the status of a patient and evaluating a rehabilitation treatment.

2.3.1 Detection of Gait Phases based on a Hidden Markov Model (HMM)

A Hidden Markov Model (HMM) for Gait Phase Analysis

A hidden Markov model (HMM) is a statistical model which is appropriate for modeling sequential data [55, 99]. Formally, the HMM is defined as a doubly embedded stochastic process with an underlying process that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce the sequence of observations [100]. This means that the states underlying the data generation process are hidden, and they can be inferred through observations. HMMs have been used successfully in many applications including speech recognition [100], gene detection [114], and gesture recognition [69, 120].

Because three gait phases in the swing motion, initial swing, mid-swing and terminal swing, cannot be distinguished by GRFs, six gait phases (Initial Contact (IC), Loading Response (LR), Mid-Stance (MS), Terminal Stance (TS), Pre-Swing (PS), and Swing phases (SW)) are used to analyze gait motions. Now, there are six hidden states in gait motions, i.e., six gait phases, and they can be observed through the sequential GRF signals from the four air-bladder sensors installed in Smart Shoes (Hallux, Meta1, Meta4, Heel). Thus, the HMM is appropriate for gait phase analysis. A graphical representation of the HMM for gait phase analysis is shown in Fig. 2.6. The state and the observations at time $t$ are denoted as $q_t$ and $y_t$, respectively. The observations ($y_t$’s) are in grey color. The six states at time $t$ are expressed by a multinomial random variable $q_t$ where $q_t = i$ ($i$=1 for IC, 2 for LR, 3 for MS, 4 for TS, 5 for PS and 6 for SW). The four observation at time $t$ are represented by $y_t^j$, where $j$=Hallux, Meta1, Meta4, Heel. A in Fig. 2.6 is a transition matrix, where the $(i,j)$th entry $a_{ij}$ represents the transition probability $p(q_{t+1} = j|q_t = i)$, i.e., the transition probability from the $i$th state at a given step to the $j$th state at the following step.
Conditional Probability with a Given Gait Phase

Due to the unique and repetitive normal GRF patterns, the normal GRF at a certain time can be approximated as a Gaussian distributed random variable by collecting many GRF data of normal gait. To obtain the mean and the variance of the Gaussian distribution, thirty six GRF data of normal gait from six subjects (age: $28.3 \pm 1.03$, six steps per subject) without any known gait disorders were collected. The subjects were asked to walk about 30∼50m at a normal walking speed (4∼5km/h) on the plain ground. The data indicated that the walking speed does not influence the magnitude of the GRF significantly if the walking speed is in the range of the normal walking speed, while the body weight was a major factor, i.e., the magnitudes of GRFs are proportionally increased with respect to the body weight. Thus, the magnitude of the GRF is normalized by the body weight. The time span of data is normalized by the stride percentage, which is distinguished by heel contact. Fig. 2.7 shows the Gaussian distribution at the hallux in one stride. The thick solid line in the bottom plane is the mean of the data, and the upper and the lower dashed lines in the bottom plane are $\pm 1.96$ standard deviation from the mean (95% confidence interval of a Gaussian distribution). Due to the large degree of freedom of the data, the $t$-distributions are approximated as a Gaussian distribution. The grey lines show the Gaussian distributions at each stride percentage.

Since four GRF signals are measured at the same time, the distribution is a multivariate Gaussian distribution as (2.1).

$$p(y|\mu,\Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\{-\frac{1}{2}(y-\mu)^T\Sigma^{-1}(y-\mu)\}$$

(2.1)

where $y$, $\mu$ and $\Sigma$ are a GRF signal vector, a mean vector and a covariance matrix, respectively. In this case, since the number of observations at the given time is four, $n=4$, $y$ is a vector in $\mathbb{R}^4$, $\mu$ is a vector in $\mathbb{R}^4$, and $\Sigma$ is a $4 \times 4$, symmetric matrix.

For the inference of gait phases, which is discussed in the next section, the conditional probability of the observation with a given state, i.e., $p(y_t|q_t)$, is required. To obtain the conditional probability, the values of $\mu$ and $\Sigma$ in (2.1) need to be classified by gait phases. When the normal
CHAPTER 2. GAIT PHASE ANALYSIS BASED ON GROUND REACTION FORCES

Gait data was obtained, the walking motions were recorded by a camcoder, and the joint angles of a lower extremity (hip, knee, and ankle) were measured by encoders and inclinometers. The gait phases were determined by recorded video and the joint angle data with skilled physical therapists. Also they were verified by the literatures [96]. Based on the gait phases from the data and the literature, the GRF data were labeled, i.e., 1~5% for IC, 6~10% for LR, 11~35% for MS, 36~55% for TS, 56~65% for PS, and 66~100% for SW. The normal GRF bands (solid lines and thin dashed lines) and the normal GRF data labeled by gait phases (thick dashed lines) at the four sensing areas in Smart Shoes are shown in Fig. 2.8.

There are several values of \( \mu \) and \( \Sigma \) in one labeled gait phase. For example, five different \( \mu \) and \( \Sigma \) are in IC since 1~5% of normal GRF data are used for the classification. To find the most likely conditional probability with those \( \mu \) and \( \Sigma \), the maximum probability is picked as the conditional probability after calculating the conditional probability in (2.1) with all \( \mu \) and \( \Sigma \) in the labeled gait phase as in (2.2).

\[
p(\mathbf{y}_t|q_t=i) = \max_{\forall \mu, \Sigma \text{ in } \{q_t=i\}} p(\mathbf{y}_t|\mu, \Sigma) \tag{2.2}
\]

where \( i \) is one of 1, \cdots, 6 for IC, LR, MS, TS, PS, and SW.

**Detection of Gait Phases**

The hidden states, i.e., gait phases, can be inferred as the posterior probability, \( p(q_t|\mathbf{y}) \). The inference problem for HMMs involves taking as input the sequence of observed data and yielding as output a probability distribution on the underlying states [55, 99]. Due to the dependence between
the states, this problem is substantially complex, but it can be readily solved by simple recursion
equations guided by Bayes rule as follows.

\[
p(q_t | y) = \frac{p(y | q_t) p(q_t)}{p(y)} \tag{2.3}
\]

\[
= \frac{p(y_0, \cdots, y_t | q_t) p(y_{t+1}, \cdots, y_T | q_t) p(q_t)}{p(y)} \tag{2.4}
\]

\[
= \frac{\alpha(q_t) \beta(q_t)}{p(y)} \tag{2.5}
\]

where

\[
\alpha(q_t) = p(y_0, \cdots, y_t | q_t) \tag{2.6}
\]

\[
\beta(q_t) = p(y_{t+1}, \cdots, y_T | q_t) \tag{2.7}
\]

and \( T \) is total experiment time. \( \alpha \) and \( \beta \) of each time step can be found by the following recursion
equations.

\[
\alpha(q_{t+1}) = \sum_{q_t} \alpha(q_t) a_{q_t, q_{t+1}} p(y_{t+1} | q_{t+1}) \tag{2.8}
\]

\[
\beta(q_t) = \sum_{q_{t+1}} \beta(q_{t+1}) a_{q_t, q_{t+1}} p(y_{t+1} | q_{t+1}) \tag{2.9}
\]
where \(a_{q_t,q_{t+1}}\) denotes the \((i, j)\) entry of the transition matrix \(A\) for \(q_t = i (i=1, \ldots, 6)\) and \(q_{t+1} = j (j=1, \ldots, 6)\). \(p(y_{t+1}|q_{t+1})\) is a conditional probability which is calculated by the method discussed in the previous chapter. For the details of the \(\alpha-\beta\) recursion method, refer [55, 99].

### 2.3.2 Detection of Abnormal Transitions in Gait Phases

Since there are six states in the HMM, the transition matrix has six rows and columns. In normal gait, the gait phases appear sequentially as the solid lines in Fig. 2.9. In other words, the state transitions in normal gait are only the transitions between adjacent gait phases, or self-transitions. Thus, the transition matrix of normal gait has the tridiagonal-like form as in (2.10).

\[
A = \begin{bmatrix}
a_{11} & a_{12} & 0 & 0 & 0 & a_{16} \\
a_{21} & a_{22} & a_{23} & 0 & 0 & 0 \\
0 & a_{32} & a_{33} & a_{34} & 0 & 0 \\
0 & 0 & a_{43} & a_{44} & a_{45} & 0 \\
0 & 0 & 0 & a_{54} & a_{55} & a_{56} \\
a_{61} & 0 & 0 & 0 & a_{65} & a_{66}
\end{bmatrix}
\]  

(2.10)

The diagonal elements in (2.10) represent the probabilities of self-transitions in gait phases, and the other non-zero elements \((a_{12}, a_{21}, a_{23}, a_{32}, \text{etc.})\) mean the transition probabilities between adjacent gait phases. The diagonal elements are almost one since most of the state transitions are self-transitions. Also the 0’s in (2.10) mean that there is no transition between non-adjacent gait phases.
This can be easily understood by Fig. 2.10. In Fig. 2.10(a), three detected gait phases, PS, SW, and IC, are depicted as an example. As shown in the figure, the self-transitions are represented as diagonal terms \(a_{55}, a_{66}, \) and \(a_{11}\), and the transitions between them are represented as \(a_{i+1, i}\) and \(a_{i, i+1}\) \(\left(a_{56}, a_{65} \right.\) and \(a_{61}, a_{16}\). If the gait phases are changed as in the dashed circle of Fig. 2.10(a), i.e., one monotonically decreases, and one monotonically increases, then there are not \(a_{i+1, i}\) terms since \((i+1)\) state appears only after \(i\) state. However, if the gait phases are changed with fluctuation as in Fig. 2.10(b), i.e., \(i\) state (PS) appears after \((i+1)\) state (SW) as in the dashed circle, then this makes \(a_{i+1, i}\). However, since these transitions rarely happen in normal gait, \(a_{i+1, i}\) terms are usually much smaller than \(a_{i, i+1}\). Also \(a_{61}\) and \(a_{16}\) of normal gait are almost zero since the state transition from SW to IC is very sudden due to the heel strike. The experimental results of normal gait will be discussed in the next section.

The sequence of the gait phases may be changed in abnormal gait as the dashed lines in the Fig. 2.9. If the gait phases are not changed sequentially, then non-zero probabilities appear between
non-adjacent gait phases. Thus, by checking the self-transition probabilities and the transition probabilities between gait phases, abnormal gait phase sequence can be detected.

The transition matrix can be estimated by the expectation-maximization (EM) algorithm as follows:

$$\hat{a}_{i,j} = \frac{\sum_{t=0}^{T} \xi_{t,t+1}^{i,j}}{\sum_{t=0}^{T} \gamma_{t}^{i}}$$  \hspace{1cm} (2.11)

where $\gamma_{t}^{i}$ denotes the posterior probability at time step $t$ with the state $i$ as in (2.3) and $\xi$ is defined as follows:

$$\xi_{t,t+1} = \xi(q_{t}, q_{t+1}) = p(q_{t}, q_{t+1} | y)$$  \hspace{1cm} (2.12)

$$= \frac{\alpha(q_{t}) p(y_{t+1} | q_{t+1}) \gamma(q_{t+1}) a_{q_{t}, q_{t+1}}}{\alpha(q_{t+1})}$$  \hspace{1cm} (2.14)

where $q_{t} = i (i=1, \cdots, 6)$ and $q_{t+1} = j (j=1, \cdots, 6)$, respectively. For the details of the EM algorithm with an HMM, see [55, 99].

### 2.3.3 Experimental Results

The proposed phase analysis methods have been applied to various GRF data. One normal GRF data and two abnormal GRF data were analyzed by the proposed methods. Two abnormal GRF data were from a Parkinson Disease patient before and after a rehabilitation treatment [4, 5, 8]. The proposed algorithm was implemented in Matlab. After obtaining the GRF data, they were analyzed by the Matlab program, which provides estimated gait phases and a state transition matrix. By checking the gait phases and the transition matrix before and after the rehabilitation treatment, the status of the patient is diagnosed, and the effectiveness of the rehabilitation treatment is evaluated. The detected gait phases by the proposed method were checked by skilled physical therapists.

### Normal Gait

Figure 2.11 shows the GRF data of normal gait with normal GRF bands. The normal GRF data in the figure is from the normal GRF data which was used to construct the normal GRF bands. The thick line represents the normal GRF data, and thin solid and dashed lines are normal GRF bands. As shown in the figure, since all GRF signals are in the 95% confidence interval of normal GRF bands, it is expected that it would give the normal gait phase pattern. The gait phases, i.e., the posterior probabilities, are estimated by (2.3) with the data, and the result is shown in Fig. 2.12. As shown in the figure, the gait phases appear sequentially with the correct order. The estimated transition matrix is shown in Table 2.1 and plotted in Fig. 2.13. The self-transition probabilities, i.e., the diagonal elements, are almost one, and the state transition occurs only between adjacent states. Thus, it has tridiagonal-like form as shown in (2.10), which means that the gait phase are changed with the correct sequences.
Figure 2.11: GRF signals (normal gait).

Figure 2.12: Estimated gait phases (normal gait).
Table 2.1: Estimated transition matrix (normal gait).

<table>
<thead>
<tr>
<th></th>
<th>IC</th>
<th>LR</th>
<th>MS</th>
<th>TS</th>
<th>PS</th>
<th>SW</th>
</tr>
</thead>
<tbody>
<tr>
<td>IC</td>
<td>0.9825</td>
<td>0.0174</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>LR</td>
<td>0.0004</td>
<td>0.9706</td>
<td>0.0288</td>
<td>0.0000</td>
<td>0.0000</td>
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</tr>
<tr>
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<td>0.0000</td>
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<td>0.9999</td>
</tr>
</tbody>
</table>

Figure 2.13: Estimated transition matrix (normal gait).
Parkinson’s Disease Patient (before a rehabilitation treatment)

Parkinson’s Disease is a degenerative disorder of the central nervous system that impairs ambulation, balance, speech, attention and other functions. It often associates with gait disorders, such as shuffling, freezing, decreased arm-swing, stooped posture and dyskinesia [86]. This patient suffered from Parkinson’s Disease involving both sides of his body. The main problem in the patient’s gait motions was shuffling. Due to the shuffling motion, the patient had a short step and insufficient foot clearance. This was followed by decreased heel strike and delayed shift from the lateral to the medial forefoot to achieve push off at the end of the stance phase.

Figure 2.14 shows the patient’s GRF signals before a rehabilitation treatment. It is observed that the GRF at the heel is much lower and the GRF at the hallux is higher than those of normal gait. Also the GRF at Meta1 is higher at the start and the end of each stride due to shuffling and the freezing gait motions.

These abnormal GRF signals make abnormal gait phases. Figure 2.15 shows the estimated gait phases of the patient. Because of the low GRF at the heel and the high GRF at the hallux, IC lasts very shortly and LR is not observed at all. Also PS is mixed with TS due to the high GRF at Meta1 at the end of each stride. These results were coincident with the observation from the physical therapists; IC, LR and PS were not clearly observed.

The transition matrix of the patient is shown Table 2.2. In a transition matrix, the probabilities in each row are normalized to make the sum of probabilities in each row be one. But, if one state does not appear at all, then the raw transition probabilities from the state to other states are
very small, which makes the normalized transition probabilities do not make sense. Thus, in this algorithm, the transition probabilities in a certain row are not normalized if the sum of the raw probabilities in the row are too low. In this case, the transition probabilities from LR to other states are not normalized since LR does not appear at all, i.e., the raw transition probabilities from LR to other states are very small.

The transition probability from IC to MS is non-zero which means that there is an abnormal gait phase transition from IC to MS. Also as explained previously, the transition probabilities from LR to other states are all zero since LR is not observed at all. The self-transition probabilities of TS and PS are smaller, and the transition probabilities between them are larger than those of normal gait. It shows that TS and PS are mixed each other. As shown in Fig. 2.16, the pattern of transition probabilities are different from those of normal gait in Fig. 2.13.

**Parkinson’s Disease Patient (after a rehabilitation treatment)**

The patient took a rehabilitation treatment with a mobile gait monitoring system (MGMS) in the PT Health and Wellness Program, the Department of Physical Therapy and Rehabilitation Science, University of California, San Francisco. The patients’ GRF signals were provided to the patient in the real-time as visual feedback information by the MGMS. For the details of the MGMS, see [4, 5, 8]. The effectiveness of the rehabilitation treatment with the MGMS is evaluated by checking the estimated gait phases and the transition matrix.
Table 2.2: Estimated transition matrix (abnormal gait, before a rehabilitation treatment).

<table>
<thead>
<tr>
<th></th>
<th>IC</th>
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<th>MS</th>
<th>TS</th>
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</tr>
</tbody>
</table>

Figure 2.16: Estimated transition matrix (abnormal gait, before a rehabilitation treatment).
Figure 2.17: GRF signals (abnormal gait, after a rehabilitation treatment).

Figure 2.17 shows the GRF data after the rehabilitation treatment with the MGMS. The GRF at the hallux is decreased, the GRF at the heel is increased, and the GRF at Meta1 is decreased at the start of each stride. Also the maximum values of GRFs at the hallux, Meta1 and Meta4 appear later due to the increased foot clearance. The GRF signals are still abnormal, but it is obvious that the shuffling motion is decreased.

The improved GRF signals make the gait phases changed as shown Fig. 2.18. The lasting time of IC is increased, and LR is observed even though it appears only in a short time. Also PS is observed more clearly than before.

As shown in Table 2.3 and Fig. 2.19, the transition matrix has been changed. The transition probabilities from LR to other states appear. The self-transition probabilities of TS and PS are increased, and the transition probabilities between them are decreased, which means that the sequence of gait phases is changed to that of normal gait. It is not easy to see how the transition matrix in Table 2.3 is abnormal comparing with the normal transition matrix in Table 2.1, but it is obvious that the transition matrix is improved toward the normal one from the transition matrix in Table 2.2.
Figure 2.18: Estimated gait phases (abnormal gait, after a rehabilitation treatment).

Table 2.3: Estimated transition matrix (abnormal gait, after a rehabilitation treatment).

<table>
<thead>
<tr>
<th></th>
<th>IC</th>
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2.4 Summary

In this chapter, a hidden Markov model (HMM) was applied to analyze gait phases. Ground reaction forces (GRFs) data from Smart Shoes were used as observed data. For the detection of gait phases, the posterior probabilities from the HMM were utilized, and the transition matrix was analyzed to check the abnormal state transition between gait phases. The proposed method was verified by three GRF data sets: one normal GRF data, two data from a Parkinson Disease patient. The experimental results showed that the estimated gait phases and the transition matrix have the potential to be used as tools for diagnosing the status of gait and checking the effectiveness of rehabilitation treatment.
Chapter 3

Monitoring Systems for Gait Rehabilitation

3.1 Introduction

The purpose of rehabilitation is to reduce instability and facilitate normal, effective and efficient patterns of gait to avoid obstacles, change direction and prevent falling. Usually gait rehabilitation treatment is coordinated by a physical therapist. Physical therapists facilitate the restoration of a normal gait pattern by providing patients with force or audio feedback during and after observing the patients’ gait pattern. One of the most important processes in the gait rehabilitation treatment is observing and timing walking to estimate step and stride length, weight shift, trunk alignment, pelvic rotation, reciprocity, symmetry and stability as the patient walks on a stable or unstable surface over ground or on a treadmill. Through clinical observation, therapists outline the parameters of dysfunction and determine an appropriate intervention strategy to improve the performance of each patient. Due to the diversity of patients’ symptoms and causes, the treatment is performed manually based on biomechanical, musculoskeletal and neuromotor principles.

This conventional gait rehabilitation treatment, however, has several drawbacks. First of all, since the treatment effect depends on physical therapists’ observation skills, basic knowledge, and experience, the effect of the treatment may be limited by the analytical ability of the physical therapist. That is, the diagnosis of patients’ gait and the evaluation of the effect of treatment are determined by only visual observation, response to exercise and manual techniques and opinion. Other than timed tests and application of ordinal scales for safety in terms of balance and quality of gait [21, 58], quantitative and graphical analyses of gait kinetics and kinematics as well as the effect of the treatment on gait parameters are generally not available in the clinical setting. Moreover, since the treatment is achieved only when the patients visit the therapist in the clinical setting, the effect of the treatment may not be as well integrated at home and in the community. Thus, a mobile gait monitoring system (MGMS) that provides the quantitative and graphical analysis on patients’ status without restriction of time and place, is desired.

The gait motions can be observed by various methods, e.g., measuring the joint angles or the foot pressures. Since the gait motion is cyclic, there are repetitive patterns in the joint motions or
the foot pressure patterns during walking. Measuring the joint angles using encoders or a camera-based method are one of the most effective methods to observe gait motions. But measuring the motion with encoders requires a cumbersome exoskeleton-type linkage to utilize the sensors. Some of the previous researchers have developed the exoskeleton-type assistive devices [48, 56, 122], but the inconvenience of exoskeletons has not been fully overcome. Moreover, despite the functionalities of exoskeleton-type linkages, such wearing devices may disturb the gait motions due to their insufficient degrees of freedom, which also reduce the accuracy of measurement. In this aspect, a camera-based method such as VICON [119] is widely used for observing gait motions. In this method, several optical markers are mounted on a human body, and cameras capture the reflected light from the markers. It produces well-quantified and accurate results on the joint motions of the lower extremity. However, the use of the camera-based method is restricted to a laboratory environment, and hard to be used in daily living. Also it requires tight clothes for marker placement which may cause patients to alter their gait.

Measuring ground reaction forces (GRFs) between the foot and the ground is another useful method for observing gait motions, since the cyclic gait motions result in repetitive and unique GRF patterns. GRFs contain necessary information for gait analysis, since the foot is the most distal part of lower extremity and it touches the ground indispensably in any shape. In other words, GRF patterns reflect abnormal gait motions. Moreover, measuring GRFs is less challenging and more practical than measuring the joint angles, as GRFs can be relatively easily measured by a force plate or installing pressure/force sensors under a shoe.

A force plate is the most popular and standard method to measure GRFs [28, 31, 59, 105]. The force plate, however, requires well-built walkways, which are not usually movable. Also only one or two steps can be measured during one trial [104, 105]. To overcome those drawbacks, the mobile GRF measurement devices have been studied, e.g., force sensors installed under a shoe. From 70’s, force transducers, usually semiconductor strain gauges, were attached to the sole of subject’s shoes by Klajic et al and Miyasaki et al, etc. [27, 59, 80]. Pappas et al. developed a gait phase detection system which uses various sensors including a force sensitive resistor (FSR) for measuring foot pressure [94]. Bamberg et al. devised a shoe-integrated wireless sensor system, which measures the foot pressure with four FSRs [16]. Morris et al. developed a shoe-integrated sensor system for wireless gait analysis and real-time feedback [83]. However, the FSR can not reflect the actual foot pressure over a large area due to its small size and the low maximum range of a FSR. Several commercial shoes which embed hundreds of FSRs provide detailed pressure distribution [88, 116], but they are redundant for gait monitoring and the assessment of gait abnormality in terms of cost-efficiency. In this aspect, Smart Shoes introduced in the previous chapter are noteworthy [3,62,67]. Smart Shoes have been devised for the detection of gait phases by measuring GRFs of the foot.

Abnormal gait can be observed by analyzing GRF patterns since there are unique and repetitive GRF patterns in normal gait, and abnormal gait results in different GRF patterns from the normal GRF patterns [85, 95, 108, 113]. Thus, abnormal gait can be observed by the raw GRFs. However, more information about abnormal gait can be observed through the center of GRF (CoGRF) since CoGRF represents the effective point of all acting GRFs, body weight transition or gait balance can be observed by the CoGRF [45, 123]. Also, the method for the evaluation of gait abnormality
is discussed in this chapter to diagnose the patients and to assess the rehabilitation treatment more accurately. The gait abnormality is evaluated based on how far the abnormal gait pattern is from the normal gait pattern in terms of GRF. In this chapter, the normal GRF pattern is defined as a GRF band considering variations in the normal GRF pattern. The normal GRF band is constructed from many experimental data of normal gait. Since the root-mean-square (RMS) value of the GRF deviation can represent the amount of GRF deviation from the normal gait patterns, gait abnormality is evaluated as the RMS value of GRF deviation. In this chapter, the MGMS is developed to collect GRF data with Smart Shoes and to monitor patients’ GRF patterns. The proposed MGMS consists of Smart Shoes as a sensing method and a micro signal processor with a touch screen display. Visual feedback information about patients’ status and the normal GRF patterns are provided so that the patients can practice the rehabilitation treatment by themselves without restriction of time and place. The proposed system analyzes the patients’ gait with the GRF data, the CoGRF, and the gait abnormality stated above. The effectiveness of the proposed gait analysis methods with the MGMS has been verified by the clinical tests with actual patients suffering from gait disorders.

The concept of the MGMS is extended to a tele-gait monitoring system which consists of an inertial measurement unit (IMU), Smart Shoes, and the Internet communication. Although the GRF patterns measured by the MGMS provide useful information for the diagnoses of a patient’s walking motions, Smart Shoes do not measure the position of the feet, which is necessary for a more detailed analysis of walking motions. In the proposed tele-gait monitoring system, an IMU is used in addition to Smart Shoes for a better observation of walking motions. By analyzing the signals measured by the IMU and Smart Shoes, it is possible to thoroughly diagnose the patient’s walking motion, including the trajectory of the foot, the walking distance, and the length of each stride. Furthermore, the proposed gait monitoring system makes use of the Internet such that physical therapists can monitor their patients’ status anywhere anytime.

### 3.2 A Mobile Gait Monitoring System

Conventional gait rehabilitation treatment does not provide quantitative information on abnormal gait kinematics, and the match of the intervention strategy to the underlying clinical presentation may be limited by clinical expertise and experience. Also the effect of rehabilitation treatment may be reduced as the rehabilitation treatment is achieved only in a clinical setting. In this chapter, a mobile gait monitoring system (MGMS) is proposed for the diagnosis of abnormal gait and rehabilitation. The proposed MGMS consists of Smart Shoes and a micro signal processor with a touch screen display. It monitors patients’ gait by observing the ground reaction force (GRF) and the center of GRF (CoGRF), and analyzes the gait abnormality. Since visual feedback about patients’ GRFs and normal GRF patterns are provided by the MGMS, patients can practice the rehabilitation treatment by trying to follow the normal GRF patterns without restriction of time and place. The gait abnormality proposed is defined by the deviation between the patient’s GRFs and normal GRF patterns which are constructed as GRF bands. The effectiveness of the proposed gait analysis methods with the MGMS has been verified by patients suffering from gait disorders.
3.2.1 Configuration of a Mobile Gait Monitoring System

The mobile gait monitoring system (MGMS) proposed in this chapter collects the GRF data and monitors patients’ gait by providing the GRFs and the CoGRF. The MGMS consists of Smart Shoes as a sensing unit and a micro processor with a touch screen display. The concept of the MGMS is shown in Fig. 3.1. A laptop was used for a mobile display and a computing system as shown in Fig. 3.1(a) [4, 5, 8, 10]. In this system, the pressure sensors for the air bladder sensors were connected to a data acquisition board by a wire, and the data acquisition board was connected to a laptop with a USB connector. Figure 3.1b shows the system flow diagram of the MGMS. The patient’s GRFs are captured by Smart Shoes ((1) in Fig. 3.1), and the measured GRF signals are transmitted to the computing and the display systems ((2) in Fig. 3.1). The measured GRFs and the normal GRF patterns are provided to patients as visual feedback information ((3) in Fig. 3.1) during the rehabilitation treatment. The patient can correct his gait by trying to follow and simulate the normal GRF patterns. After the rehabilitation treatment, the MGMS analyzes the patient’s gait by evaluating his gait abnormality based on the GRF deviation from the normal GRF band.

Figure 3.2 show the actual implementation of the proposed MGMS [5, 8, 10]. Intelligent Display Module of Luminary Micro [76] acts as a data acquisition board, a computing system and a mobile display as shown Intelligent Display Module box in Fig. 3.1b. The Intelligent Display of MGMS is shown in Fig. 3.2a. Intelligent Display Module used for the system has a 32-bit ARM Cortex-M3 Core and a 70 mm touch screen display. The GRF signals measured by Smart Shoes are transmitted to this module via a wire which is plugged in the LAN connector in Fig. 3.2b, and GRFs are displayed on the screen. The GRF data are saved at the micro SD card in the module for the analysis after the rehabilitation treatment. The size of the MGMS is about 70×90×40 mm and the weight is about 200 g including batteries. The mobility of the MGMS allows patients to take advantage of the gait monitoring device in their daily lives.

3.2.2 Observation of Abnormal Gait

Raw GRF signal

Figure 3.3 shows typical GRF signals of the normal gait with body weight 68kg measured by Smart Shoes. The time axis is normalized by stride percentage which starts from the stance phase. The start of the stance phase is detected by checking the rise of sum of GRFs, and it is usually done by checking the GRF at the heel in normal walking. At the first contact up to 20% of stride, the GRF of the heel goes over about 120% of body weight because of the impact force at heel contact. From about 20% of stride, the GRFs of the Meta1 and the Meta4 appear, which means that these parts start contacting the ground. The sum of GRFs stays around body weight during 30~50% of one stride, i.e., when the body is supported by only this foot. After about 65% of one stride, the sum of GRFs is about zero, which means that the foot is in the air.

Abnormal gait motion can be observed by the GRF signals measured by Smart Shoes. For example, if a patient has insufficient knee extension at the heel strike, then the GRF of the heel
(a) Concept of a Mobile Gait Monitoring System (MGMS)

(b) System flow diagram of the MGMS

Figure 3.1: Concept of a Mobile Gait Monitoring System (MGMS).
CHAPTER 3. MONITORING SYSTEMS FOR GAIT REHABILITATION

Figure 3.2: Implementation of a Mobile Gait Monitoring System (MGMS).

Figure 3.3: Raw GRF signals in normal gait (body weight: 68kg).
would be lower than that in normal gait. More detailed analysis from actual patients’ data will be discussed in Chapter 3.2.6.

**Center of GRF**

Since four GRFs are measured by Smart Shoes, the center of GRF (CoGRF) in \(x\) and \(y\) directions can be calculated by the following equations.

\[
\begin{align*}
\text{CoGRF}_x &= \frac{\sum x_i GRF_i}{\sum GRF_i} \quad (3.1) \\
\text{CoGRF}_y &= \frac{\sum y_i GRF_i}{\sum GRF_i} \quad (3.2)
\end{align*}
\]

where \(x\) and \(y\) axes are in the lateral and sagittal axis, respectively, \(i (1 \sim 4)\) corresponds to each of hallux, Meta1, Meta4, and heel, \(x_i\) and \(y_i\) shown in Fig. 3.4(a) are the distance from an ankle to \(i\) part in the \(x\) and \(y\) directions, and \(GRF_i\) is the GRF of the \(i^{th}\) part. The origin is located at the point of the ankle projected on the foot surface. Figure 3.4(a) shows the change of CoGRF from actual GRF data of normal gait, and Fig. 3.4(b) shows the CoGRF in \(x\) and \(y\) directions. The CoGRF in \(x\) direction starts from the center of the foot and moves slightly outside of the foot and ends at the hallux. The CoGRF in \(y\) direction moves from the heel to the hallux; it stays at the heel up to 20% of the stride, and stays at the hallux between 40% and 65%. This CoGRF change in \(y\) direction occurs because the heel and the hallux act as hinges at those times. Since the CoGRF shows an effective point of whole acting GRFs, the transition of body weight or the body balance can be observed through the change of CoGRF [45, 123].

Since the accuracy and reliability of the air bladder sensor of Smart Shoes were verified by the experiment in Chapter 2, it is evident that the CoGRF is accurate, because the distance between the sensors is fixed. For more precise verification, the CoGRF in Fig. 3.5 by Smart Shoes was validated by comparing the CoGRF by a force plate with a VICON system [119]. Two force plates from Advanced Mechanical Technology Inc. [2] were used to measure GRFs and ten infrared cameras and markers from VICON were used to analyze the foot motion. For the collection of the data, VICON Nexus program was used. The origin of the coordinate, i.e., the point of the ankle projected on the foot surface, was calculated from two markers on the ankle shown in Fig. 3.5a. One of the healthy subject whose data was used for constructing the normal GRF bands in Fig. 3.6 was requested to walk on the force place of the VICON system with normal walking speed while wearing Smart Shoes. The CoGRF data from Smart Shoes and the force plate with the VICON system were collected at the same time. The experimental results are given in Fig. 3.5b. The gray dots in the figure represents the CoGRF by the force plate with VICON, and the black dots in the figure stand for the CoGRF by Smart Shoes. Note that the CoGRF by Smart Shoes is located inside the boundary formed by the center of the air-bladder sensors. It is observed that two CoGRFs are almost the same except at the heel and around the hallux. Since the subject walked on the force
CHAPTER 3. MONITORING SYSTEMS FOR GAIT REHABILITATION

plate wearing Smart Shoes, the CoGRF was observed from the contact of the heel of the shoe. Also due to the stiffness of the shoe, the CoGRF ended at the front point of the shoe, not at the hallux.

3.2.3 Evaluation of Gait Abnormality

Normal GRF bands

To evaluate gait abnormality by GRF patterns, a standard GRF pattern needs to be identified. Since there is a variance in the GRF even in the same walking conditions, the normal GRF pattern should be constructed as a band, which represents an acceptable range of normal gait. The magnitude of GRF at the four sites of Smart Shoes are influenced by the body weight and the walking speed. For example, as the body weight increases, the GRF increases as well. The higher walking speed may result in larger GRF due to the increased impact force. Also the walking speed changes the period of one stride. To obtain the normal GRF band, thirty six GRF data of normal gait from six subjects (age: 28.3 ± 1.03, six steps per subject) without any known gait disorders are collected. The subjects were asked to walk about 30~50m at a normal walking speed (4~5km/h) on the plain ground. The data indicated that the walking speed does not influence the magnitude of the GRF significantly if the walking speed is in the range of the normal walking speed, while the body weight was a major factor, i.e., the magnitudes of GRFs are proportionally increased with respect to the body weight. Thus, the magnitude of the GRF is normalized by the body weight. The time span of data is normalized by the stride percentage which starts from the stance phase.

Figure 3.6 shows normal GRF bands at the four sensing areas in Smart Shoes obtained from the
(a) Smart Shoes with markers (in red circles)  
(b) CoGRF by Smart Shoes and a VICON system (gray dots: by VICON, black dots: by Smart Shoes)

Figure 3.5: CoGRF verification with a VICON system.

Figure 3.6: Normal GRF bands (solid lines: mean, dashed lines: ± 2.03 SD).
experimental data. The solid line is the mean value of the data, and the upper and the lower dashed lines are ±2.03 standard deviation from the mean (95% confidence interval using t-distribution with 35 degrees of freedom). This normal GRF band is used as the criterion for normal gait as a reference for patients with gait abnormalities. That is, if a GRF signal is in this band, then it is considered as a normal GRF signal. Otherwise, it is considered as an abnormal GRF signal. In Fig. 3.6, the GRF band at the Meta4 is wider than the other parts. This observation is because the body is supported by one leg when the GRF at the Meta4 increases.

### Gait abnormality based on GRF deviation

An objective value that shows the gait abnormality is required to diagnose patients’ gait and to assess the effect of gait rehabilitation treatment. The measure for gait abnormality proposed in this chapter is evaluated based on how far the GRFs are from the normal GRF patterns. The normal GRF bands constructed in the previous section are used as the normal GRF patterns. Figure 3.7(a) is one example (GRF at the heel of patient B before the rehabilitation treatment in Chap. 3.2) which shows the GRF deviation from the normal GRF bands. The thick line in the figure is actual GRF data from a subject, and the GRF bands are calculated by multiplying his/her body weight to the normal GRF bands which are shown in Fig. 3.6. The arrows in the figure mean the GRF deviation from the normal GRF bands, and they are plotted in Fig. 3.7(b). Positive or negative deviation means that the GRF is larger or smaller than the normal GRF band, respectively. Since the root-mean-square (RMS) value of the GRF deviation from the normal GRF band implies the gait abnormality discussed above, the RMS value of the GRF deviation normalized by the body weight is used as gait abnormality. Namely,

\[
GA = \frac{1}{BW} \sqrt{\frac{1}{n} \sum_{i=1}^{n} (GRF_i)^2} \tag{3.3}
\]

where \(GA\) is the gait abnormality, \(BW\) is the body weight, \(n\) is the number of total data, and \(GRF_i\) is the \(i^{th}\) GRF deviation. The gait abnormality is calculated by the following steps. 1) obtaining GRF data from a subject, 2) multiplying the normal GRF bands with his/her body weight, 3) obtaining GRF deviations from the normal GRF bands, and 4) calculating the gait abnormality based on (3.3).

### 3.2.4 Participants

Seven Parkinson’s Diseases patients (age: 61.4 ± 15.2 years, 4 male/3 female) who were participating in a motor control and gait program at the PT Health and Wellness Center, the Department of Physical Therapy and Rehabilitation Science, University of California, San Francisco, were included in this study. As a screening process, severely impaired patients who needed walking aids were excluded in the experiments since the patients were required to move their body by themselves during the proposed rehabilitation treatment. Patients with cognitive deficits were also
excluded because the patients needed to understand the proposed system and to follow the visual information given by the MGMS during the rehabilitation treatment. All patients who participated in the experiments walked abnormally at a glance, but the symptoms of abnormal gait and degree of abnormality were all different. Informed consent forms approved by the Institutional Review Boards for the University of California at Berkeley and San Francisco were provided to all participants.

### 3.2.5 Rehabilitation Treatment Procedures

The rehabilitation treatment with MGMS was performed at the PT Health and Wellness Program, the Department of Physical Therapy and Rehabilitation Science, University of California, San Francisco. Two physical therapists supervised the whole experiments for any emergency situations. Before the rehabilitation treatment with MGMS, explanations about the rehabilitation treatment with the MGMS such as configuration of the system, visual feedback information, etc. were provided. The patient wore Smart Shoes and walked 20m on a plain ground without the MGMS and the GRFs were measured by Smart Shoes (this will be called ‘Before applying MGMS’ in the captions of the following figures). Then visual feedback information was provided to patients during the rehabilitation treatment. Patients needed some times to be accustomed to the system, but after several practices, they could easily adapt to the MGMS. After the adaptation period, patients walked on the same walkway with visual feedback information about their GRFs and normal
3.2.6 Results and Discussion

In this chapter, the patients’ GRFs before and after the rehabilitation treatment with the MGMS are analyzed using CoGRF and the proposed gait abnormality. The results of the representative three cases are discussed first, then results of whole participants are presented.

Patient A

Parkinson’s Disease is a degenerative disorder of the central nervous system that impairs ambulation, balance, speech, attention and other functions. It is often associated with gait disorders, such as shuffling, freezing, decreased arm-swing, stooped posture and dyskinesia [86].

Patient A suffered from Parkinson’s Disease involving both sides of his body. The main problem was shuffling and freezing. This patient had a short step and insufficient foot clearance followed by decreased knee flexion and ankle dorsi flexion during the swing phase. This was followed by poor pelvic rotation, decreased heel strike and delayed shift from the lateral to the medial forefoot to achieve push off at the end of the stance phase. Since both feet showed similar GRF patterns, only the GRF signals from the left foot have been analyzed.

Figure 3.8(a) shows GRFs and their sum, and Fig. 3.9(a) shows GRFs of Hallux, Meta1, Meta4 and Heel of the foot (thick solid line) with the normal GRF band (thin solid line and dashed lines) before the rehabilitation treatment with the MGMS. The graphs show that the magnitude of GRF at the heel is lower than that of normal gait, and the GRFs of the hallux, the Meta1, and the Meta4 appear earlier compared with the normal GRF bands before the rehabilitation treatment. Also a peak value in the sum of GRFs, which is supposed to appear at about 20% of stride, is not present. These GRF patterns can explain his abnormal gait motions; low GRF at the heel is caused by “sliding” of the foot and poor toe off. The shuffling motion removes the peak value in the sum of GRFs at about 20% of stride. Also GRFs at the hallux, the Meta1, and the Meta4 appear early, since the sliding of the foot is associated with early touching of the forefoot. These abnormal gait motions can also be observed through the CoGRF. Figure 3.10(a) shows the change of CoGRF before the rehabilitation treatment with the MGMS. It is observed that the CoGRF does not pass the heel and it stays more at the hallux before the rehabilitation treatment, which is caused by the same abnormal gait motions.

After the rehabilitation treatment with the proposed MGMS, his GRF patterns have been changed. As shown in Fig. 3.8(b) and Fig. 3.9(b), GRF at the heel increases and GRFs at the hallux and the Meta1 become closer to the normal GRF bands. The CoGRF passes the ankle and stays less at the hallux, as shown in Fig. 3.10(b). Table 3.1 shows the gait abnormality calculated
Figure 3.8: GRF data (Patient A).
Figure 3.9: GRF with normal GRF bands (Patient A).
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Table 3.1: Gait Abnormality (Patient A).

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>After</th>
<th>Improvement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hallux</td>
<td>0.07</td>
<td>0.06</td>
<td>14.29</td>
</tr>
<tr>
<td>Meta1</td>
<td>0.07</td>
<td>0.06</td>
<td>14.29</td>
</tr>
<tr>
<td>Meta4</td>
<td>0.02</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Heel</td>
<td>0.26</td>
<td>0.22</td>
<td>15.38</td>
</tr>
<tr>
<td>Mean</td>
<td>0.11</td>
<td>0.09</td>
<td>18.18</td>
</tr>
</tbody>
</table>

by (3.3). The gait abnormality shown in Table 3.1 indicates that his gait patterns become closer to the normal gait patterns. Hallux, Meta1 and Heel show improvement in the gait abnormality, but Meta4 does not show noticeable improvement within the precision of the system. Considering the change in his gait pattern after applying MGMS, i.e., increased rolling over and heel strike, the improvement of the gait abnormality in Hallux, Meta1 and Heel can be understood.

Patient B

Patient B also suffered from Parkinson’s Disease. Her symptoms included increased rigidity and a tremor of the right arm, limiting her arm swing, and rigidity in the lower right limb. The rigidity was associated with a short step and decreased foot clearance in the swing phase followed by decreased hip extension, pelvic rotation, hip flexion, knee flexion and ankle dorsi flexion. Similar to Patient A, it was difficult for her to strike the heel and smoothly transfer her body weight from
the lateral foot to the medial foot prior to toe off.

The GRF data in Fig. 3.11(a) and Fig. 3.12(a) show that her whole foot touches the ground at the same time. The sum of GRFs in Fig. 3.11(a) reaches its maximum at about 50% of stride and decreases because she touches the ground with her whole foot without rolling over due to her stiff foot. The CoGRF stays only around the middle foot as shown in Fig. 3.13(a) because of the decreased foot clearance. After the rehabilitation treatment with the MGMS, the sequence of GRFs, which is the same as normal gait is observed, i.e. the GRF at the heel, the Meta4, the Meta1, and the hallux appears in sequence as shown in Fig. 3.11(b). The GRFs stay in the normal GRF band more than before as shown in Fig. 3.12(b). However, the GRF at the heel still appears late. This means that the rolling over of the forefoot is still not adequate. The CoGRF has also been improved; it moves from the heel to the hallux as shown in Figs. 3.13(b). Table 3.2 shows the gait abnormality calculated by (3.3) before and after the rehabilitation treatment with the MGMS. Gait abnormalities of Hallux, Meta1 and Heel are increased, which means that her gait pattern become closer to the normal GRF patterns by increased rolling over and foot clearance.

### Patient C

Patient C also suffered from Parkinson’s Disease. His gait motions seemed to be normal at a glance, but he rarely used the inside of the foot because of his knee problem. Figure 3.14(a) shows that the GRF at the Meta1 is smaller, and the GRF at the Meta4 is larger than those of normal gait. Figure 3.15(a) shows that the GRF of the Meta1 is the most changed from the normal GRF band. Since the inside of his foot rarely touches the ground, the CoGRF does not move enough to the inside of the foot and does not end at the hallux as shown in Fig. 3.16(a). After the rehabilitation treatment, the GRF at the Meta1 increases and the GRF at the Meta4 decreases as shown in Fig. 3.14(b), and they are contained more in the normal GRF bands as shown in Fig. 3.15(b). The CoGRF analysis in Fig. 3.16(b) shows that the CoGRF moves more to the inside of the foot. Table 3.3 shows the significant improvement in his gait pattern.

### All Patients

The proposed rehabilitation treatment with the MGMS was applied to seven Parkinson’s Disease patients, and the result of whole patients is presented in Table 3.4. As shown in the table, GRFs
Figure 3.11: GRF data (Patient B).
Figure 3.12: GRF with normal GRF bands (Patient B).
CHAPTER 3. MONITORING SYSTEMS FOR GAIT REHABILITATION

Figure 3.13: CoGRF (Patient B).

Table 3.3: Gait Abnormality (Patient C).

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>After</th>
<th>Improvement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hallux</td>
<td>0.07</td>
<td>0.03</td>
<td>57.14</td>
</tr>
<tr>
<td>Meta1</td>
<td>0.11</td>
<td>0.05</td>
<td>54.54</td>
</tr>
<tr>
<td>Meta4</td>
<td>0.17</td>
<td>0.03</td>
<td>82.35</td>
</tr>
<tr>
<td>Heel</td>
<td>0.14</td>
<td>0.08</td>
<td>42.86</td>
</tr>
<tr>
<td>Mean</td>
<td>0.12</td>
<td>0.05</td>
<td>58.33</td>
</tr>
</tbody>
</table>
Figure 3.14: GRF data (Patient C).
Figure 3.15: GRF with normal GRF bands (Patient C).
CHAPTER 3. MONITORING SYSTEMS FOR GAIT REHABILITATION

Table 3.4: Gait Abnormality (seven patients).

<table>
<thead>
<tr>
<th></th>
<th>Before (Mean ± SD)</th>
<th>After (Mean ± SD)</th>
<th>Improvement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hallux</td>
<td>0.08 ± 0.01</td>
<td>0.07 ± 0.02</td>
<td>12.50</td>
</tr>
<tr>
<td>Meta1</td>
<td>0.11 ± 0.02</td>
<td>0.09 ± 0.03</td>
<td>18.18</td>
</tr>
<tr>
<td>Meta4</td>
<td>0.09 ± 0.06</td>
<td>0.05 ± 0.03</td>
<td>44.44</td>
</tr>
<tr>
<td>Heel</td>
<td>0.29 ± 0.11</td>
<td>0.23 ± 0.11</td>
<td>20.69</td>
</tr>
<tr>
<td>Mean</td>
<td>0.14 ± 0.04</td>
<td>0.11 ± 0.05</td>
<td>21.43</td>
</tr>
</tbody>
</table>

of all parts show improvement in terms of the gait abnormality calculated by (3.3). Since each patient showed improvement at different parts depending on their abnormal gait motions, the mean values of improvements in each part might not have significant meaning. The mean values of improvements of all parts, however, imply that patients’ GRFs were improved about 21% to the normal GRF patterns even though patients showed improvement at different parts. While the improvement presented in this section is encouraging, there are further problems to be addressed from rehabilitation treatment. Such problems will be discussed in the last section of this chapter.

3.3 A Tele-Monitoring System for Gait Rehabilitation

Gait rehabilitation treatment is usually performed manually by a physical therapist in a rehabilitation facility. The therapist observes and diagnoses the condition of a patient, and applies an
appropriate action for gait rehabilitation. Since the rehabilitation process requires periodic observations of the patient’s gait behavior, the patient is required to frequently revisit the rehabilitation facility. The recent development of the mobile communication system allows the rehabilitation treatment to happen with fewer visits to the rehabilitation facility.

The mobile gait monitoring system (MGMS) in the previous chapter has been developed to monitor a patient’s ground reaction forces (GRFs) and evaluate the status of a patient \([4, 5, 8, 10]\). The MGMS utilized a shoe-type GRF measurement system, called Smart Shoe, which embeds air-bladders under the insole and measures the pressure changes in the air-bladders \([62, 67]\). Although the GRF patterns measured by the MGMS provide useful information for the diagnoses of patients’s walking motions, Smart Shoes do not measure the position of feet, which is necessary for a complete diagnosis of walking motions. Moreover, this system cannot provide rehabilitative assistance to the patient without the presence of a physical therapist.

In this chapter, a tele-gait monitoring system with an inertial measurement unit (IMU) and Smart Shoes is proposed \([12]\). By analyzing the signals measured by the IMU and the force sensors of Smart Shoes, it is possible to thoroughly diagnose the patients walking motion, including: the trajectory of the foot, the walking distance, and the length of each stride. Moreover, the use of the IMU with Smart Shoes allows the gait rehabilitation treatment under natural conditions in daily lives. Treadmills have been widely used in gait rehabilitation treatments since they allow for easy observation of a patient’s motions and convenient control for treatment settings. However, many researchers have found that walking motions on a treadmill are different from those on the ground due to the lack of the transition motions of the center of body weight \([1, 71]\). Also, the treadmill does not fully realize arbitrary environments in daily lives, which limits the effectiveness of rehabilitation treatment. In the proposed system, the measured and estimated information on the patient’s status is sent to the physical therapist in a rehabilitation facility via the Internet. The status of a patient is monitored by a physical therapist and an appropriate rehabilitation treatment can be prescribed in real-time.

### 3.3.1 System Configuration

The proposed tele-gait monitoring system for gait rehabilitation consists of Smart Shoes and an inertial measurement unit (IMU) as shown in Fig. 3.17. As discussed in the previous chapter, a mobile gait monitoring system (MGMS) was developed using a micro processor equipped with a touch screen and Smart Shoes \([4, 5, 8, 10]\). As a mobile system, the MGMS provided useful information for diagnosing the patient’s walking status, but more data are required for a complete diagnosis of walking motions. Moreover, this system cannot provide rehabilitative assistance to the patient without the presence of a physical therapist. In this system, an IMU is utilized with Smart Shoes to measure the position of the feet for more detailed information about the walking motions of a patient.

There have been active research on utilizing inertial navigation systems for indoor tracking without GPS \([42, 54, 91]\). An IMU usually has accelerometers, gyroscopes and magnetometers to measure accelerations, angular velocities and magnetic fields in the body frame which is a local
Figure 3.17: A tele-gait monitoring system for gait rehabilitation with Smart Shoes and an IMU.

coordinate of the sensor. The motion in the navigation frame, which is a universal coordinate, is estimated by the sensor measurements in the body frame and the rotation matrix. The rotation matrix, which shows the coordinate relationship between the body frame and the navigation frame, is estimated by the signals from gyroscopes and magnetometers [42, 54, 91]. The position and velocity in the body frame are calculated by integrating the accelerations in the navigation frame which are converted from the accelerations in the body frame using the rotation matrix. The proposed tele-gait monitoring system uses 3DM-GX2 from MicroStrain [77], which has a three axis accelerometer, a three axis gyroscope and a three axis magnetometer. Since it provides the estimated rotation matrix by its own algorithm, the rotation matrix is not estimated by the raw signals of gyroscopes and magnetometers.

In the proposed tele-gait monitoring system, the measured and estimated quantities are transmitted to a physical therapist via the Internet. The use of the Internet enables better rehabilitation services anywhere anytime by providing immediate guidance for rehabilitation treatments and alerts for emergency situations. The network platform for the tele-gait rehabilitation system is divided into two levels; a local processing level and a global processing level. At the local processing level, simple signal processing algorithms for Smart Shoes and the IMU such as measuring GRFs and the gait phase detection method are implemented. A graphic user interface for physical therapists to monitor their patients’ status and motion patterns are implemented in the global processing level. The two levels are connected by the Internet. The concept of the tele-gait monitoring system is shown in Fig. 3.18.

3.3.2 Monitoring Gait Motions

Estimation of Position

In the navigation system, the body frame is a local frame attached to a sensor and the navigation frame is a universal frame as shown in Fig. 3.19. Any quantities measured in the body frame can
be converted to those in the navigation frame by the rotational matrix, \( M \), as follows.

\[
x_n = M' x_b
\]  

(3.4)

where \( x_n \) and \( x_b \) represent the quantities in the navigation frame and the body frame, respectively.

The rotational matrix can be estimated by gyroscope and magnetometer measurements \([42, 54, 91]\). Since the rotational matrix is directly available from 3DM-GX2, the rotational matrix is not estimated by the signals from gyroscopes and magnetometers. The output of an accelerometer, \( y_a \), can be expressed as

\[
y_a = a_b + v_a + M \cdot g
\]  

(3.5)

where \( a_b \) is true angular acceleration in the body frame other than gravitational acceleration, \( v_a \) is noise in output, and \( g \) is the acceleration of gravity. The acceleration in the navigation frame can be calculated by

\[
a_n = M' \cdot y_a - g
\]  

(3.6)

The velocity and the position in the navigation frame, \( v_n \) and \( r_n \), can be estimated by integrating the acceleration of (3.6). In the discrete time domain, they are calculated as follows.

\[
v_n(k) = v_n(k - 1) + \frac{T}{2} (a_n(k) + a_n(k - 1))
\]  

(3.7)

\[
r_n(k) = r_n(k - 1) + \frac{T}{2} (v_n(k) + v_n(k - 1))
\]  

(3.8)

where \( k \) is an index and \( T \) is a sampling time.
Once the position of the foot is estimated, other supplementary information such as the length of each stride and the walking speed can also be calculated. The stride length is calculated by the distance between consecutive heel strikes which is detected by Smart Shoes, and the walking speed is calculated by the stride length divided by the elapsed time during each step.

**Zero Velocity Update**

Since the estimate of the velocity and position obtained by integrating the acceleration signal diverge, it is not possible to estimate the position and velocity for more than a few seconds using inertial sensing alone. To prevent the divergence of the estimate, a zero velocity period, which is guaranteed to have zero velocity, is used. During the zero velocity period, the velocity is assumed to be zero, thus, the velocity is reset to zero.

In the proposed system, the zero velocity periods are determined by the gait phases detected by Smart Shoes. Previously, a fuzzy logic has been applied for the estimation of the gait phases in normal gait using GRFs measured by Smart Shoes [62, 67]. One example of the detected gait phases is shown in Fig.3.20(a). Each value of gait phases represents the probability of each gait phase. Since the IMU is attached in the forefoot, the forefoot should not be moved during the zero velocity period. Thus, the mid-stance (MS) and the terminal stance (TS) phases are used as the zero velocity period as shown in Fig. 3.20(b).

The zero velocity periods are validated by accelerometer signals from the IMU as shown in Fig. 3.21. The zero velocity periods are marked as gray color in Fig. 3.21. The accelerations from the IMU are almost zero in the periods, which means that the forefoot does not move.
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Figure 3.20: A zero velocity period determined by Smart Shoes.
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Experimental Results

The performance of the proposed system and algorithms have been experimentally verified. A healthy male subject without known gait disorders was instructed to walk while wearing Smart Shoes with the IMU. Raw sensor signals from the system such as GRFs, accelerations, and angular velocities were measured from Smart Shoes and the IMU. The gait phases, a foot position, stride lengths, and walking speeds were estimated in real-time.

Figure 3.22 shows the experimental results for foot position tracking. The healthy subject was asked to walk on flat grounds around a building. The size of the walking path was about 20m × 25m, and it was identified by grids on the ground. Even though fluctuations of the foot position were observed in every step due to the error update during the zero velocity periods, the system was still able to track the rectangular position correctly. Also, the foot clearance, which is very important for observing the abnormal gait, can be estimated by the z directional position. Figure 3.22(d) shows the foot clearance in five steps. Figure 3.23 shows the calculated stride length and the walking speed during the experiment. The average of stride length and the walking speed were 1.009 m and 0.659 m/s, respectively.

3.3.3 Real-time Data Transfer via the Internet

The proposed tele-gait monitoring system is connected to medical specialists by an Internet-based network. The proposed system allows the medical specialists to monitor their patients’ status anywhere at any time and to provide better rehabilitation services. It is able to provide immediate
Figure 3.22: Experimental results: tracking of the foot.
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The network platform for the tele-gait rehabilitation system is divided into two levels; a local processing level and a global processing level. The gait phase and its abnormality detection methods are implemented at the local processing level. The signal processing algorithms for the IMU introduced in the previous section are also at the local processing level. Algorithms at the global processing level include a graphic user interface for physical therapists to monitor their patients’ status and motion patterns and to provide an interactive guidance for a better result of rehabilitation. In addition, more demanding applications such as joint torque estimation are to be implemented at the global level.

The two levels are connected by the Internet. The extensive infrastructure of the Internet, including the wireless Internet available at many public areas, makes it possible for physical therapist to access the monitoring system carried by a patient anywhere at any time. However, the Internet protocol does not guarantee real-time communication, which is necessary for the tele-gait monitoring system. If data is shared in real-time without a buffer on the Internet platform, packet-loss and time-delay may occur. The packet-loss and time-delay make the use of the Internet for the
The characteristics of the Internet-based monitoring are investigated by experiments. Fig. 3.24 shows the raw ground reaction force signals measured by Smart Shoes and the signals transferred by the Internet. The common IEEE 802.11 wireless local area network was used for the communication. The update rate was 100 Hz; the sampling time was 0.01 sec. It is shown in the figure that the transferred data is often not updated and is held by the previous value due to the packet-loss. Since the communication protocol returns the value of the previous step when the packet-loss occurs, the transferred data can also be regarded as delayed data with an unknown time-delay constant. Note that the intervals between the updated points are not regular. In particular, the irregularity of the time interval is severe if wireless Internet is used.

3.4 Summary

In this chapter, a mobile gait monitoring system (MGMS) was proposed to monitor patients’ gaits and provide accurate and objective information on gait abnormality. The proposed MGMS has advantages because 1) it can analyze patients’ gaits with quantitative and graphical methods, which improve the planning of the appropriate intervention strategy 2) patients can practice the rehabilitation treatment without restriction of time and place. The proposed MGMS consists of Smart Shoes as sensing units, and a micro controller with a display. The ground reaction force (GRF) measured by Smart Shoes and the center of GRF (CoGRF) are used for monitoring abnormal gait. Gait abnormality proposed in this chapter is calculated as the root-mean-square (RMS) value of the GRF deviation from the normal GRF bands, which implies how far the GRFs are from the normal GRF patterns. Patients can correct their gait by trying to adapt their GRFs to normal GRF patterns based on the video feedback information from the MGMS. It is verified that abnormal gait can be diagnosed and improved by the MGMS from the results of the clinical tests. Therapists can then focus their attention on limitations in flexibility, strength and motor control which may be
remediated by specific exercises for flexibility, strengthening and motor learning.

Even though all patients showed improvement in their GRFs by the proposed rehabilitation treatment with the MGMS, there are several limitations for the system. First of all, severely impaired patients who needed walking aids could not be improved by the proposed system. For those patients, body weight supporting gait rehabilitation system [73] may be helpful for their gait rehabilitation since they can move their lower extremity easily by the supporting system. Also we have found that the patient’s walking tended to become unstable when the patient concentrated too much on the visual feedback of the MGMS. To avoid distraction by the visual feedback, audio feedback such as beeping sounds or detailed voice instruction will be applied so that the patients are able to stabilize their body by vision while receiving information for rehabilitation through audio.

The concept of the MGMS was extended to a tele-monitoring system utilizing the Internet. The tele-gait monitoring system with an inertial measurement unit (IMU) and Smart Shoes was proposed. The system monitors the patient’s status using the information measured by Smart Shoes and the IMU. GRFs measured by Smart Shoes and the estimated gait phases are the basic information for monitoring the patient’s status. The estimated position of the foot, the stride length and, the walking velocity are also available by the IMU. The position of the foot is calculated by integrating the acceleration signals from the IMU after converting them to the navigation frame. Zero velocity periods determined by gait phases are utilized for updating velocity errors. The measured and estimated information is transmitted to medical specialists by the Internet. The Internet-based network system is able to provide immediate and personalized physical therapy in real-time.
Chapter 4

Control of Assistive Systems for Rehabilitation

4.1 Introduction

Assistive systems for rehabilitation with actuation capabilities have been intensively developed in recent years based on mechatronic and robotic technologies [17, 17, 22, 30, 37, 46, 48, 49, 56, 87, 106, 118, 122, 124]. In the design and control of such assistive systems for rehabilitation, it is necessary to consider precise torque generation, low output-impedance, compactness and light weight, which are directly related to the comfort, safety, and practicality of the system. To account for these requirements, electric motors equipped with gear reducers have been widely utilized in the assistive systems. However, not only do the gear reducers amplify the motor torque by reducing the rotor speed, but they also increase the mechanical impedance of the system significantly. In addition, nonlinearities inherent in the gear reducers (e.g., friction and backlash) and modeling uncertainties make the precise torque control challenging.

To overcome such drawbacks of the geared motors while taking advantage of their superior controllability and high power-mass density, various types of actuator systems have been proposed in the previous work [9, 60, 61, 63, 64, 66]. Previously, a rotary series elastic actuator (RSEA) and a compact series elastic actuator (cRSEA) have been developed, which employ a series elastic mechanism [92, 97, 98, 102]. Unlike the other series elastic actuator which utilizes an electric motor and a linear spring, a torsional spring is applied to the RSEA and the cRSEA. The torsional spring placed between the actuator and the human joint plays the role of a torque sensor as well as an energy buffer, and the use of a torsional spring allows more compact design for the assistive systems.

In this chapter, nonlinear control algorithms for the RSEA and the cRSEA are exploited to generate the desired torque precisely in the presence of nonlinear resistive factors and modeling uncertainty. By the proposed control algorithms, the inertia, damping, and friction of the geared motor are effectively rejected by precisely controlling the spring deflection. Sliding mode control
smoothed by a boundary layer is applied to overcome the nonlinearities and enhance the robustness for the modeling uncertainties. The thickness of the boundary layer is changed by gait phases in order to minimize the torque error without the chattering phenomenon.

In addition to the precise generation of the desired assistive torque, safety is another important requirement in assistive systems for rehabilitation. Vulnerable users may get injured or feel pain by a sudden impact, i.e. large assistive torque or fast change in the assistive torque from the systems. In the rehabilitation systems, the desired torque is determined in real-time based on measurements that represent the patient’s status, the impact may occur during the operation of the rehabilitation system. In this chapter, control algorithms which utilize a proxy between the desired position and current position of the actuator as a safety buffer are discussed to prevent impacts from the rehabilitation system. The actuator tracks the proxy as accurate as possible with a sliding mode controller, which compensates for the modeling uncertainties and nonlinearities in the actuator.

In spite that the impedance of the motor could be reduced remarkably by the proposed nonlinear controller, the mass of the actuators could not be rejected and was imposed to the human body. To separate actuators from a human body, a cable-driven human assistive system has been developed [7, 65]. In the system, the assistive torque is transmitted via cables from the actuators to the end-effector which is to be attached on a human joint. The use of cables in flexible tubes allows for users to move freely without carrying the heavy actuators. However, the varying cable friction according to the curvature of the flexible tubes sets a challenge on the precise generation of the desired torque. To generate the desired torque precisely, a hierarchical control scheme is applied to the system. The hierarchical control scheme is divided into two main controllers: a high level controller and a low level controller. In this chapter, the higher level controller which determines cable tensions corresponding the desired assistive torque, is discussed.

4.2 Gait Phase-Based Sliding Mode Control for a Rotary Series Elastic Actuator

As applications that involve physical human-robot interaction (pHRI), such as power augmentation or rehabilitation systems, are gaining great attentions, actuators for pHRI have been investigated actively. Actuators for ideal pHRI are controlled in a force/torque mode, which requires compensation of the inherent mechanical impedance including nonlinear friction. The nonlinear relation between the control input and the generated torque output also obstructs the natural pHRI.

Series elastic actuators have been proposed to fulfill the requirements of actuators for pHRI [92, 97, 98, 102]. The springs utilized in the series elastic actuators enable compensation of the mechanical impedance inherent in electric motor systems. In previous work [9, 61, 63, 64], a rotary series elastic actuator (RSEA) was proposed based on the similar principle but with a torsional spring. The performance of series elastic actuators, including the RSEA, depends on the algorithm that controls the deflection of the spring. Such control algorithms play the role of the lowest level controller in pHRI systems to generate the desired torque accurately.
The control of series elastic actuators is challenged by the inherent nonlinear frictions in geared motor systems and modeling uncertainty. In this chapter, nonlinear control algorithms are exploited for the RSEA to generate the desired torque accurately in the presence of nonlinear resistive factors and modeling uncertainty. In general, the design of nonlinear control algorithms is more straightforward than linear robust controllers for systems with known nonlinearities. For example, the nonlinear Coulomb friction in the RSEA can be directly rejected by the nonlinear control input. In this chapter, the sliding mode control is applied since it shows better robustness for modeling uncertainty than the feedback linearization control. However, the chattering phenomenon caused by the sliding mode controller should be avoided for natural pHRI. By applying a boundary layer around the sliding surface, the chattering effect can be decreased, but it makes tracking performance deteriorated. Since the desired motor angle is dependent on the human motions, the thickness of the boundary layer is changed according to human motions to minimize the tracking error without chattering phenomena. The RSEA is installed on the knee joint and the thickness of the boundary is changed by two major gait phases, i.e., swing and stance phases. The performance of the proposed control algorithm is verified by experiments with actual human walking motions.

4.2.1 A Rotary Series Elastic Actuator (RSEA)

Design of a Rotary Series Elastic Actuator (RSEA)

A rotary series elastic actuator (RSEA) has been proposed for assisting human motions [9, 61, 63, 64]. The RSEA shown in Fig. 4.1 consists of a DC motor, a torsional spring, and two encoders each on the human side and the motor side. The torsional spring is used to generate the desired torque, and acts as an energy buffer between the actuator and the human joint. The similar approaches are shown in [92, 97, 98, 102], where they applied a linear spring for the same purpose. Since a linear spring requires torque arms for generating torque, a torsional spring is directly installed between the human joint and the motor in the design of the RSEA. The position of the DC motor is controlled to have the proper spring deflection such that the RSEA generates the desired torque precisely. The joint angle is limited by the angle limiter to protect the patient in case of a malfunction. The overall design is shown in Fig. 4.1.

Since the spring installed in the RSEA is utilized as a torque sensor as well as a torque transmitter, the performance of RSEA depends on characteristics of the spring. In general, a spring is a nonlinear element, i.e. the spring force is a nonlinear function of the spring deflection. Since the transmitted torque is estimated by the spring deflection in this application, the nonlinearity may affect the control performance, i.e. the actual transmitted torque may be different from the estimated torque. To check the nonlinearity of the spring, an experiment was performed. The body of RSEA was fixed on the ground such that the frame ((c) in Fig. 4.1) presses a loadcell for measurement of the transmitted force. The force is converted into the torque by multiplying the torque arm, i.e. the length of the frame. Fig. 4.2 shows the experimental results of the relation between the spring deflection and the measured torque. It is desired that the curve is a straight line that passes through the origin. As shown in the figure, the spring used in the experiment shows very good linearity in
the desired deflection range. The stiffness blows up at a certain deflection angle (see -25 degrees in the figure) because the spring is mechanically constrained. Since the relation shown in the figure is close to linear in the desired deflection range, the spring is regarded as a linear elements.

Identification of Motor Resistive Torque

The actuating torque is generated by a DC motor in the RSEA. Motors have been widely used in applications involving human-robot interaction due to their superior controllability and flexibility. The capacity of a motor is defined by the maximum allowable power, i.e. a multiplication of the angular velocity and the generated torque. Since a motor has physical limitations on the maximum velocity and the maximum torque, the operation range is adjusted by a reduction ratio. The use of reducers introduces various nonlinearities such as friction and backlash. The generated torque is magnified by the reduction ratio, but the rotor inertia and the friction force are also amplified significantly. The resistive torque is undesirable characteristics for pHRI actuators since a human has to make an additional effort to overcome the resistive torque. Also nonlinear resistive torque introduced by a gear reducer makes the accurate generation of the desired torque difficult. Thus the resistive torque should be compensated for improved pHRI.

The measured resistive torque in the RSEA is shown in Fig. 4.3. The output torque was measured by a torsional spring. In an ideal case, the resistive torque should be zero regardless of the angular velocity when the control input is zero (labeled Target in Fig. 4.3). However, due to the friction force, there is a resistive torque in actual device (labeled Actual in Fig. 4.3). Note that the magnitude of the bias force is so large that the motor rotates even under zero control input. This
phenomenon often occurs in applications of DC motors. The discontinuity at zero angular velocity represents the Coulomb friction force. The resistive torque shown Fig. 4.3 is modeled as follows.

\[
\tau_{\text{resistive}} = a_1 + a_2 \text{sgn}(\dot{\theta}_M) + a_3 \dot{\theta}_M \tag{4.1}
\]

where the coefficients \(a_1\), \(a_2\), and \(a_3\) represent terms due to bias, nonlinear friction, and linear damping, respectively. The values of \(a_1\), \(a_2\), and \(a_3\) were found using a curve fitting method with given data, and the values are shown in Table 4.1.

<table>
<thead>
<tr>
<th>Coefficient (Unit)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_1) (Nm)</td>
<td>(-1.509 \times 10^0)</td>
</tr>
<tr>
<td>(a_2) (Nm)</td>
<td>(9.572 \times 10^{-1})</td>
</tr>
<tr>
<td>(a_3) (Nm/(\text{rad/sec}))</td>
<td>(1.414 \times 10^{-1})</td>
</tr>
</tbody>
</table>

4.2.2 Nonlinear Controller Design for a Rotary Series Elastic Actuator

System Modeling

A schematic diagram of the RSEA installed on a human joint is depicted in Fig. 4.4. \(I_M\) is the inertia of the motor, and \(\theta_M\) and \(\theta_H\) are the angles of the motor and the human joint, respectively. \(\tau_M\) represents the motor torque, and \(\tau_{\text{resistive}}\) is the resistive torque. The motor and the human joint are connected via a torsional spring with spring constant \(k\), and the controlled output is the spring torque which is proportional to the spring deflection, i.e., the difference between the motor and the
Figure 4.3: Experimental results for the motor friction test [64].

Figure 4.4: Schematic plot of the human joint and the RSEA.
CHAPTER 4. CONTROL OF ASSISTIVE SYSTEMS FOR REHABILITATION

human joint angle. The following relation is obtained from Fig. 4.4 by applying Newton’s law and Hooke’s law,

\[ I_M \ddot{\theta}_M = \tau_M(t) + k(\theta_H - \theta_M) - \tau_{\text{resistive}} \]  \hspace{1cm} (4.2)

where \( \tau_{\text{resistive}} \) is defined in (4.1). For a state space system model, let \( x_1 = \theta_M, x_2 = \dot{\theta}_M, u = \tau_M \), and \( y = x_1 \). Then, the resulting state space system equation is,

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= -\frac{k}{I_M}x_1 + \frac{1}{I_M}u - \frac{\tau_{\text{resistive}}}{I_M} + \frac{k}{I_M}\theta_H \\
y &= x_1
\end{align*}
\]  \hspace{1cm} (4.3)

Feedback Linearization

The feedback linearization control technique algebraically transforms a nonlinear system into a linear one such that linear control methods can be applied [110]. The nonlinearities in the system is canceled by the feedback linearization control input, thus the closed-loop dynamics is in a linear form. To define the control law for the feedback linearization controller, the output \( y \) is differentiated until the control input \( u \) appears. In case of the system in (4.3), the control input \( u \) appears in the second derivative of \( y \), which means the relative degree of the system is two.

\[
\begin{align*}
\dot{y} &= \dot{x}_1 = x_2 \\
\ddot{y} &= \dot{x}_2 = -\frac{k}{I_M}x_1 + \frac{1}{I_M}u - \frac{\tau_{\text{resistive}}}{I_M} + \frac{k}{I_M}\theta_H \equiv v
\end{align*}
\]  \hspace{1cm} (4.5)

where \( v \) is the synthetic input. To determine the synthetic input, a pole placement method is applied, i.e.

\[
v = -c_0(y - y_d) - c_1(\dot{y} - \dot{y}_d) + \ddot{y}_d \]  \hspace{1cm} (4.6)

The values of \( c_0 \) and \( c_1 \) are chosen such that the equation is asymptotically stable: i.e., \( c_0 > 0 \) and \( c_1 > 0 \) in (4.6). Thus the overall control input for feedback linearization is

\[
u = I_M \cdot \left(v + \frac{k}{I_M}x_1 + \frac{\tau_{\text{resistive}}}{I_M} - \frac{k}{I_M}\theta_H\right) \]  \hspace{1cm} (4.7)

Note that the human joint angle, \( \theta_H \), appears in the feedback linearization control law. This contributes to compensation of the human factors imposed on the motor side. However, there are drawbacks in feedback linearization such as 1) it requires accurate model parameters, and 2) there exists internal dynamics if the relative degree is smaller than the dimension of the system. The internal dynamics is problematic if it is unstable. The internal dynamics does not exist in the present problem, since the relative degree is equal to the dimension of the system. The requirement of an exact model, however, may cause problems in actual implementation since there is always modeling inaccuracy in the nominal model.
Robustness Enhancement by Sliding Mode Control

The drawback of the feedback linearization control, i.e., the requirement of accurate model parameters, can be overcome by sliding mode control. Sliding mode control deals with modeling uncertainty by applying additional terms to a nominal model [110]. In this section, the design of a typical sliding mode controller for the system in (4.3) is reviewed briefly. Given the spring deflection \( E = \theta_M - \theta_H \), the error between the actual and the desired deflection and its derivative are defined as follows.

\[
\varepsilon = E - E_d = (\theta_M - \theta_H) - (\theta_{Md} - \theta_H) = \theta_M - \theta_{Md} \tag{4.8}
\]

\[
\dot{\varepsilon} = \dot{\theta}_M - \dot{\theta}_{Md} \tag{4.9}
\]

where \( E_d \) is the desired spring deflection to generate the desired torque. The sliding surface, \( S \), is defined by

\[
S = \left( \frac{d}{dt} + \lambda \right) \varepsilon = \dot{\varepsilon} + \lambda \varepsilon \tag{4.10}
\]

where \( \lambda \) is a positive constant. To assure that the tracking error, \( \varepsilon \), converges to zero, the sliding variable must converge to zero, which takes place if,

\[
S\dot{S} < -\eta |S| \tag{4.11}
\]

where \( \eta \) is a positive constant. \( \dot{S} \) can be calculated as follows.

\[
\dot{S} = (\dot{\theta}_M - \dot{\theta}_M) + \lambda (\dot{\theta}_M - \dot{\theta}_{Md}) = -\frac{k}{I_M} x_1 - \frac{a_3}{I_M} x_2 - \frac{a_2}{I_M} \text{sgn}(x_2) - \frac{a_1}{I_M} \theta_H - \dot{\theta}_{Md} + \frac{1}{I_M} u + \lambda (\dot{\theta}_M - \dot{\theta}_{Md}) \tag{4.12}
\]

\[
f(x) + CE(x) + b \cdot u
\]

where

\[
f(x) = -\frac{k}{I_M} x_1 - \frac{a_3}{I_M} x_2 - \frac{a_2}{I_M} \text{sgn}(x_2) - \frac{a_1}{I_M} \theta_H - \dot{\theta}_{Md} \tag{4.13}
\]

\[
CE(x) = \lambda (\dot{\theta}_M - \dot{\theta}_{Md}) \tag{4.14}
\]

\[
b = \frac{1}{I_M} \tag{4.15}
\]

The parameters in \( f(x) \) and \( b(x) \) are to be obtained by system identification. However, the assumed model shown in (4.3) may not fully reflect the actual dynamics due to modeling uncertainties. Therefore, \( f(x) \) and \( b(x) \) may depend on unmodeled dynamics and time varying dynamics as well.
as the nominal dynamics. Thus suppose \( f(x) \) and \( b(x) \) are composed of the nominal model \( \hat{f}(x) \) and \( \hat{b}(x) \) and uncertain parts \( \Delta f(x) \) and \( \Delta b(x) \), respectively: i.e.,

\[
\begin{align*}
\dot{f}(x) &= \hat{f}(x) + \Delta f(x) \quad (4.16) \\
\dot{b} &= \hat{b} \cdot \Delta b \quad (4.17)
\end{align*}
\]

It is assumed that \( \Delta f(x) \) and \( \Delta b(x) \) are state dependent, and that their upper bound can be found as follows.

\[
\begin{align*}
|\Delta f(x)| &\leq \alpha(x) \quad (4.18) \\
\frac{b_{\min}}{b} &\leq |\Delta b| \leq \frac{b_{\max}}{b} \quad (4.19)
\end{align*}
\]

A control input \( u \) that satisfies the condition in (4.11) is

\[
u = \frac{1}{b(x)}[-\hat{f}(x) - CE(x) - K \cdot \text{sgn}(S)]
\]

where \( K \) is chosen to guarantee the condition (4.11) such that the system is properly controlled even in the presence of modeling uncertainties. To select a proper \( K \), the following worst cases for \( \Delta f(x) \) and \( \Delta b(x) \) are assumed, i.e.

\[
\begin{align*}
\Delta f(x) &= \alpha(x) \quad (4.21) \\
\Delta b &= \frac{b_{\min}}{b} \equiv \beta_{\min} \quad (4.22)
\end{align*}
\]

Then \( K \) can be given by

\[
K = \frac{(1 - \beta_{\min})(\hat{f}(x) + CE(x)) + \alpha + \eta}{\beta_{\min}}
\]

The control law in (4.20) with \( K \) in (4.23) always satisfies the condition in (4.11). Note that once \( S = 0 \) is achieved, the error \( \varepsilon(t) \) converges to zero for any \( \lambda > 0 \) and \( 1/\lambda \) is the time constant of the error convergence. However, since the control law is discontinuous across the sliding surface \( (S = 0) \), it introduces chattering, which is not desirable in general. In particular, the noise and vibration caused by the chattering phenomenon are not desirable in the pHRI application.

**Gait Phase-Based Smoothed Sliding Mode Control**

To reduce the chattering phenomenon in the sliding mode control, a saturation function shown in Fig. 4.5 is often applied instead of a signum function. Outside of the boundary layer \( \Phi \), the control law is chosen to satisfy the condition in (4.11), which guarantees that the boundary layer is attractive. And trajectories starting inside the boundary layer remain inside the boundary layer [110].

The control input of the smoothed sliding mode control is given by

\[
u = \frac{1}{b}[-\hat{f}(x) - CE(x) - K \cdot \text{sat}(\frac{S}{\Phi})]
\]
By applying the saturation function instead of the signum function, the chattering phenomenon can be decreased, but the tracking performance is deteriorated. By adjusting the thickness of the boundary layer, the chattering phenomenon and the tracking error can be traded off. That is, if the thickness of the boundary layer is close to zero, then the controller acts like the sliding mode controller with a signum function, which shows more chattering and less tracking error. On the contrary, if the thickness of the boundary layer is large, then the chattering phenomenon disappears but the tracking performance is much deteriorated. The torque output of the RSEA, \( \tau \), depends on the spring deflection between the motor and the human joint, i.e.

\[
\tau = k(\theta_M - \theta_H) \tag{4.25}
\]

where \( k \) is the spring constant. Given the desired torque, \( \tau_d \), the desired spring deflection is \( \frac{\tau_d}{k} \). Then the desired motor angle, \( \theta_{Md} \), is determined by

\[
\theta_{Md} = \frac{\tau_d}{k} + \theta_H \tag{4.26}
\]

Note that the desired motor angle is dependent on the human joint angle as in (4.26) since the appropriate spring deflection is required to generate the desired torque. When the human joint moves fast with a large angle change, the desired motor angle trajectory is also large and changes fast, which makes the tracking error large. To decrease the tracking error without chattering phenomenon, the thickness of the boundary layer needs to be adjusted according to human motion. In the experiment, the RSEA is installed on the knee joint and the thickness of the boundary layer is changed according to two major gait phases, i.e., swing and stance phases. In the swing phase, the movement of the knee joint is large and fast, which makes the tracking error large. On the contrary, the knee hardly moves in the stance phase. Thus the boundary layer is set thinner in the swing phase than in the stance phase as shown Fig. 4.6 to decrease the torque error without the chattering phenomenon. The actual value of the thickness of the boundary layer in each phase,
\( \Phi_{\text{SW}} \) and \( \Phi_{\text{ST}} \), is adjusted manually since discomfort feeling caused by the chattering phenomenon and tracking error must both be considered. Also the boundary layer is changed smoothly as shown in Fig. 4.6 to avoid discomfort feeling when the thickness of the boundary layer is changed.

The swing and stance phases are detected by Smart Shoes [3, 62, 67]. Smart Shoes measure the ground reaction forces (GRFs) by four force sensing units embedded under the insole. In the swing phase, all GRFs are zero since the foot is in the air. In the stance phase, the sum of the GRFs indicates the body weight since the whole body weight is transferred to the foot. At the heel strike phase (the first phase of the stance phase), the sum of the GRFs is over the body weight due to the impact force at the heel strike. In the experiment in the next section, if the sum of the GRFs is greater than 5% of the body weight (body weight is about 650 N in the experiment), the human is considered in a stance phase. Otherwise he/she is regarded in a swing phase.

### 4.2.3 Performance Analysis by Experiments

**Smoothed Sliding Mode Control**

The performance of the smoothed sliding mode control is verified by comparing with that of typical sliding mode control. In this experiment, the performance of smoothed sliding mode control is verified comparing with that of sliding mode control. The desired spring deflection was set to sine wave with an amplitude of 1 rad at 1 Hz, and arbitrary motions were given to the human joint side. Figure 4.7 shows the experimental results with sliding mode control with control input in (4.20) and smoothed sliding mode control with the control input in (4.24). The motor moves around the human joint to make appropriate spring deflection for the generation of the desired joint torque. The generated torque is calculated by the spring deflection multiplied by the spring constant \( k \) [64]. As shown in Fig. 4.7(a), sliding mode control with the signum function shows extremely high tracking performance, but the high frequency chattering phenomenon is observed as shown in the tracking error graph in Fig. 4.7(a). The vibration and noisy sound by the chattering effect can be easily felt from the human side, which is highly undesirable for pHRI. Smoothed sliding mode control shows a slightly worse performance comparing to pure sliding mode control.
Table 4.2: RMS values of torque error in swing and stance phases.

<table>
<thead>
<tr>
<th></th>
<th>Swing</th>
<th>Stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed boundary layer (Nm)</td>
<td>0.1283</td>
<td>0.0558</td>
</tr>
<tr>
<td>Varying boundary layer (Nm)</td>
<td>0.0984</td>
<td>0.0507</td>
</tr>
</tbody>
</table>

as shown in Fig. 4.7(b), but the chattering phenomenon is not observed.

**Gait Phase-Based Smoothed Sliding Mode Control**

The experiments in Fig. 4.7 show the performance of the smoothed sliding mode controller without actual human motions. To verify the performance of the proposed method, i.e., the smoothed sliding mode controller with a varying boundary layer on an actual human, the experimental setup shown in Fig. 4.8 was utilized. One RSEA was installed on the knee joint, and controlled by the proposed control algorithm. The subject wearing this experimental setup walked on a treadmill at about 1.5 km/h. The desired joint torque pattern in one stride is given in Fig. 4.9. Just after the heel strike, the knee torque to the flexion direction is applied for the subject to bend the knee easily, and the knee torques to the flexion or the extension directions are applied in turn to help the knee motions in a swing phase.

The experimental result with actual walking motion is shown in Fig. 4.10. The experimental results with a constant boundary layer are shown in Fig. 4.10(a). The spring is deflected appropriately by the motor angle change. The torque error is large when the leg is in swing phases as shown in Fig. 4.10(a) due to the large and fast knee motion. The large torque error can be decreased by reducing the thickness of the boundary layer in the swing phase. Figure 4.10(b) shows the experimental result with a varying boundary layer. The thickness of the boundary layer is reduced only in the swing phases and remains the same in the stance phase. The root-mean-square (RMS) values of the torque error of each control algorithm in each phase are calculated, and the values are shown in Table 4.2. The RMS values of the torque error in the stance phase for the fixed boundary layer and the varying boundary layer are almost the same since the thickness of the boundary layer is the same, but the RMS values of the torque error in the swing phase is significantly decreased by reducing the thickness of the boundary layer.

Previously, a disturbance observer has been applied to control the RSEA [63, 64]. In terms of tracking error, both robust controllers, a disturbance observer and a sliding mode controller, showed similar performances. But the performance of each controller may be affected by design parameters in each controller: the cut-off frequency of $Q$ filter in the disturbance observer and the thickness of the boundary layer in the sliding mode controller. By designing the parameters in an optimal manner, both controller can achieve the desired performance.
Figure 4.7: Experimental results: the desired torque is set as a sinusoidal wave.
Figure 4.8: The RSEA and Smart Shoes installed on the orthosis.

Figure 4.9: Desired knee joint torque profile in one stride.
Figure 4.10: Experimental results with actual walking motions.
4.3 Control Algorithms for Prevention of Impacts in Assistive Systems

During the operation of the rehabilitation system, a sudden impact may be applied to the patient by an additional torque from the assistive system, and the patient should be protected from the sudden impact in any situations since he/she may get injured or feel pain by the impact. The impact, which is defined as a high force applied over a short period, can be prevented by a safe trajectory of the desired assistive torque, i.e., limited maximum force and slow rate for the applied torque. The rehabilitation algorithm that determines the desired torque trajectory is primarily in charge of making a smooth desired torque trajectory. However, the desired assistive torque trajectory is determined in real-time depending on the current status of the patient and the measurements from sensors. Therefore, smooth desired torque trajectory is not guaranteed, and impacts may occur due to sensor noise or sudden changes in the patient’s motion. To further avoid impact in any situations, a secondary method in the motion controller of the actuator is proposed in this chapter.

In previous work [9, 60, 61, 63, 64, 66], force/torque mode control and back-drivability were achieved by robust control algorithms such as a disturbance observer (DOB) or a sliding mode controller (SMC), but those controllers only care about the accurate generation of the desired torque without considering safety. In this chapter, control algorithms to prevent impacts are investigated by utilizing a proxy as a safety buffer between the desired trajectory and current trajectory of the actuator to adjust the rate of assistive torque and limit the maximum torque [11]. The position of proxy exponentially converges to the desired position with an appropriate rate, while the actuator follows the proxy as accurate as possible. A sliding mode controller is applied to the actuator to follow the proxy accurately while overcoming the modeling uncertainties and nonlinear effects caused by interaction with a human body. Therefore the proposed algorithm consists of a proxy and a sliding mode controller. For the verification of the proposed control algorithms, a compact rotary series elastic actuator (cRSEA) installed on the knee joint of the lower extremity orthosis is used.

4.3.1 Safety Issues in Assistive Systems

A healthy person generates sufficient joint torques by controlling muscles to achieve desired motions. The brain coordinates and controls the whole motions as a controller, and the muscles generate the required force for the desired motions. Patients with musculoskeletal disorders, however, cannot generate or control appropriate muscular forces for the desired motions. The rehabilitation treatments help the patients restore the original functions of the nerve or muscular systems by repetitive practices of normal motions.

Robotic rehabilitation systems imitate the functions of physical therapists by providing video/audio or force feedback to patients. For lightly impaired patients who can move their body comparatively easily, systems which provide video/audio feedback about ground reaction forces [4] or joint angles may be enough to help them rehabilitate by themselves. It provides the extended methods
Figure 4.11: Block diagrams of rehabilitation systems interacting with a human body.
such as video/audio signals to recognize patients’ status as shown in Fig. 4.11(a), and the feedback information can also be utilized to monitor the patients’ status [4, 73].

Monitoring may not be enough for seriously impaired patients who cannot move their body easily. They need assistive torques to follow the normal motion patterns. An active rehabilitation system applies an assistive joint torque, $\tau_A$, to augment the patient’s own joint torque, $\tau_H$. The concept of the active rehabilitation system is shown in Fig. 4.11(b). The control of the active rehabilitation system can be divided into two parts: a rehabilitation algorithm and a motion controller of an actuator. The rehabilitation algorithm determines the desired assistive torque, $\tau_{Ad}$, based on an appropriate rehabilitation strategy which may depend on physical therapist’s experience and extensive information about the patient’s status. The objective of the motion controller is to let the actuator generate the desired assistive torque precisely. An appropriate motion controller minimizes the mechanical impedance of the actuator and makes the actuator back-drivable [9, 66].

If the rehabilitation system is only for monitoring, there are few safety issues in the system. On the other hand, safety should be thoroughly considered the case of active rehabilitation systems. The patients get injured or feel pain when the amount of the assistive joint torque is excessively large or the assistive joint torque changes drastically. The rehabilitation algorithm primarily takes the charge of generating safe (i.e. bounded and smooth trajectories) trajectories of the desired assistive joint torque. Furthermore, there should be a secondary method in the motion controller to further improve patients’ safety, since unexpected situations such as a power cut may introduce safety problems even with the safe enough trajectories.

### 4.3.2 A Compact Rotary Series Elastic Actuator (cRSEA)

#### Design of a Compact Rotary Series Elastic Actuator (cRSEA)

Since the proposed control method is applied to a compact rotary series elastic actuator (cRSEA), the cRSEA is briefly introduced in this chapter. In the previously designed rotary series elastic actuator (RSEA), a spring was directly installed between the shaft of the geared motor and the human joint, but a spring is installed in the chain of gears in the cRSEA. The use of a small spring contributes to the compact design of the system.

Figure 4.12 shows the cRSEA and its mechanism. It consists of 1) a DC motor, 2) a worm gear set, 3) a spur gear set, 4) a torsional spring, 5) two high resolution encoders, 6) a motor driver, and 7) an embedded micro controller (Luminary Stellaris LM3S8962 board [75]). In the cRSEA, a worm gear is used as well as spur gears to amplify the torque generated by an electric motor. Considering the knee joint torque and velocity [6], a motor of 150 W, RE40 DC motor of Maxon Motor Company [84], was selected. The speed reduction ratio was selected to 60:1, where 10:1 comes from the worm gear and the worm wheel and 6:1 comes from the spur gears.
Figure 4.12: Compact rotary series elastic actuator (cRSEA) and its mechanism.

Kinematic and Dynamic Analysis

The power transmission mechanism of the cRSEA is shown in Fig. 4.12. The torque generated by the motor is amplified by two sets of gears, the worm gear set and the spur gear set. The knee frame is connected to the calf brace, while the main frame is fixed on the thigh brace, i.e., $\theta_H$ represents the knee joint angle. The motor angle, $\theta_M$, and the angle of the small spur gear, $\theta_S$, are measured by high resolution encoders.

The torque output of the cRSEA is given by

$$\tau_O = N_S k (\theta_W - \theta_S)$$

(4.27)

where $N_S$ is a gear ratio of the spur gear, $k$ is a spring constant, $\theta_W$ is the angle of the worm gear, and $\theta_S$ is the angle of the spur gear. In the actual design, $N_S = 6$. The knee joint angle, $\theta_H$, can be obtained, i.e.

$$\theta_H = N_S^{-1} \theta_S$$

(4.28)

Similarly, a pair of the worm gear and the worm wheel provides the speed reduction ratio of $N_W$. When the worm gear rotates one revolution, one pitch of the worm wheel is rotated. Therefore, the worm gear acts as a single toothed gear, and thus the gear ratio is the same as the number of teeth of the worm wheel. Since one revolution of the worm gear corresponds to one pitch of the worm wheel, the following kinematic condition is satisfied.

$$2\pi r_{wg}[\tan \phi]^{-1} = 2\pi w_{ww} N_W^{-1}$$

(4.29)
where $r_{wg}$ and $r_{ww}$ are the radii of the worm gear and the worm wheel, respectively. $\phi$ is the distortion angle of the worm gear [66]. Note that (4.29) can be simplified to $N_W = \frac{r_{ww}}{r_{wg}} tan \phi$.

By the dynamic analysis of the system [60, 66], the torque output is,

$$\tau_O = N_S A(\phi, \mu)[\tau_M - \left(\frac{I_{ww}}{N_W A(\phi, \mu)} + I_M \ddot{\theta}_M\right) - \tau_H]$$  \hspace{1cm} (4.30)

where

$$A(\phi, \mu) = \frac{r_{ww}(sin \phi + \mu cos \phi)}{r_{wg}(cos \phi + \mu sin \phi)}$$  \hspace{1cm} (4.31)

$A(\phi, \mu)$ in (4.31) is a torque amplification ratio of the worm gear and the worm wheel. In the cRSEA, the distortion angle of the worm gear, $\phi$, is fixed, but the friction coefficient, $\mu$, may vary depending on the lubricant or temperature conditions. Note that the torque amplification ratio is the same as the speed reduction ratio, when the friction coefficient is zero, i.e., $A(\phi, 0) = N_W = \frac{r_{ww}}{r_{wg}} tan \phi$. However, in the presence of friction, a power loss occurs and the torque is not amplified as desired. The variation in the torque amplification ratio introduces model uncertainties to the system. $N_W$ is used as a nominal value of $A(\phi, \mu)$ in the design of the control algorithm in the following chapters. By letting $I_E = \frac{I_{ww}}{N_W A(\phi, \mu)} + I_M$, (4.27) and (4.30) are combined

$$\tau_O = N_S N_W^{-1} k \theta_M - N_S^2 k \theta_H$$  \hspace{1cm} (4.32)

$$= N_S A(\tau_M - I_E \ddot{\theta}_M) - \tau_H$$  \hspace{1cm} (4.33)

By the system identification [60, 66], $I_E$ was identified as $4.255 \times 10^{-4} kg \cdot m^2$, and this value is used as a nominal value of the motor inertia in the following control algorithm.

### 4.3.3 Control Algorithms for Prevention of Impacts

**A proxy as a safety buffer to prevent impacts**

The assistive torque of the cRSEA is generated by the spring deflection caused by the position difference between the human joint and the motor as in (4.27). Thus, the generated torque can be controlled by the motor position, where the desired motor position is determined from (4.27) with a given desired assistive torque, $\tau_{Ad}$, by utilizing the relationships of $\theta_W = N_W^{-1} \theta_M$ and $\theta_S = N_S \theta_H$, where $\theta_M$ and $\theta_H$ represent the angles of the motor and the human joint, respectively. From $\tau_{Ad}$, the desired motor position, $\theta_{Md}$, is

$$\theta_{Md} = N_W (N_S \theta_H + \frac{\tau_{Ad}}{N_S k})$$  \hspace{1cm} (4.34)

As shown in (4.34), the desired position of the motor is calculated by the human joint angle and the desired assistive torque that is determined in real-time depending on the current status of the patient and the measurements from sensors. A rehabilitation algorithm generates the smooth trajectory of the desired assistive torque, but the safety of the generated trajectory is not guaranteed by sudden
changes in human motions or unexpected accidents. In this chapter, a secondary method in the motion controller to protect the user from impacts in any situations is proposed as follows. To enhance safety, a proxy is placed between the desired motor position and the current motor position as a safety buffer. The rate of the assistive torque is adjusted by the proxy, while the motor follows the proxy as accurate as possible. The proxy position is determined based on the desired motor position and the convergence rate as follows.

\[
\theta_P = \theta_{Md} + H \theta_P
\]

where \( \theta_{Md} \) and \( \theta_P \) are the desired motor position and the proxy position, respectively. \( H \) defined the convergence speed of \( \theta_P \) to \( \theta_{Md} \). \( H \) is the time constant for convergence. Note that if \( H = 0 \), then \( \theta_P \) is the same as \( \theta_{Md} \). The proxy converges to the desired motor position exponentially with a parameter \( H \). The amount of the applied torque is regulated by limiting the maximum spring deflection as follows.

\[
|\theta_{WP} - \theta_S| < E_{max}
\]

where \( \theta_{WP} \) and \( E_{max} \) are the worm gear position determined by the proxy and the maximum spring deflection, respectively. By limiting the maximum spring deflection for safety, not only does the proxy enhance the safety of human-robot interaction, but the mechanical system including the motor and spring are also protected from a damage.

**Design of a Sliding Mode Controller**

Since the cRSEA is exposed to interaction with a human body and modeling uncertainties, a robust control method is required. In this chapter, a sliding mode controller is applied to the motor to follow the proxy as accurate as possible and improve robustness for the human motions. The sliding mode controller deals with the modeling uncertainties by applying additional terms to a nominal model [110]. From the system modeling equations in (4.32) and (4.33), let \( x_1 = \theta_M \),
\( x_2 = \dot{\theta}_M \) and \( u = \tau_M \), then (4.32) and (4.33) become

\[
\begin{align*}
\dot{x}_1 & = x_2 \\
\dot{x}_2 & = -\frac{N_W^{-1}k}{AI_E}x_1 + \frac{1}{I_E}u + \frac{1}{AI_E}N_Sk\theta_H \\
& \quad - \frac{1}{N_SAI_E}\tau_H \\
\theta_M & = x_1
\end{align*}
\] (4.37)

Let the spring deflection, \( E = \theta_W - \theta_S \), then

\[
\begin{align*}
\varepsilon & = E_d - E = (\theta_{W,d} - \theta_S) - (\theta_W - \theta_S) \\
& = N_W^{-1}(\theta_{p} - \theta_M) \\
\dot{\varepsilon} & = N_W^{-1}(\dot{\theta}_{p} - \dot{\theta}_M)
\end{align*}
\] (4.40)

where \( E_d \) and \( \theta_{W,d} \) are the desired spring deflection and the desired worm gear position, respectively. Note that \( \theta_{Md} \) is determined by the proxy position, \( \theta_{p} \). The sliding variable, \( S \), is defined as,

\[
S = \left( \frac{d}{dt} + \lambda \right)\varepsilon = \dot{\varepsilon} + \lambda\varepsilon
\] (4.42)

\[
= N_W^{-1}[(\dot{\theta}_p - \dot{\theta}_M) + \lambda(\theta_p - \theta_M)]
\] (4.43)

where \( \lambda \) is a positive constant. To assure that the errors in the spring deflection, \( \varepsilon \), converges to zero, the sliding variable must converge to zero, which is guaranteed if

\[
SS < \eta|S|
\] (4.44)

where \( \eta \) is a positive constant. \( \dot{S} \) is calculated as,

\[
\dot{S} = N_W^{-1}\left[\frac{N_W^{-1}k}{AI_E}x_1 - \frac{1}{I_E}u - \frac{1}{AI_E}N_Sk\theta_H \right]
\] (4.45)

\[
+ \frac{1}{N_SAI_E}\tau_H + \dot{\theta}_p + \lambda(\theta_p - x_2)
\]

\[
= f(x) + CE(x) + b \cdot u
\] (4.46)

where

\[
f(x) = N_W^{-1}\left[\frac{N_W^{-1}k}{AI_E}x_1 - \frac{1}{I_E}u - \frac{1}{AI_E}N_Sk\theta_H \right]
\] (4.47)

\[
+ \frac{1}{N_SAI_E}\tau_H + \dot{\theta}_p
\]

\[
CE(x) = N_W^{-1}\lambda(\theta_p - x_2)
\] (4.48)

\[
b = -\frac{N_W^{-1}}{I_E}
\] (4.49)
Since the uncertainties lie in $A$ and $I_E$, $f(x)$ and $b$ can be divided into nominal parts and uncertain parts.

\begin{align}
  f(x) &= \hat{f}(x) + \Delta f(x) \\
  b &= \hat{b} \cdot \Delta b
\end{align}

The uncertain parts, $|\Delta f(x)|$ and $|\Delta b|$, are bounded by

\begin{align}
  |\Delta f(x)| &\leq \alpha(x) \\
  \beta_{\text{min}} &\leq |\Delta b| \leq \beta_{\text{max}}
\end{align}

where $\beta_{\text{min}} = \frac{b_{\text{min}}}{b}$ and $\beta_{\text{max}} = \frac{b_{\text{max}}}{b}$. $\alpha(x)$, $b_{\text{min}}$, and $b_{\text{max}}$ represent the boundaries of the uncertain parts in $f(x)$ and $b$, respectively, and they can be found by inserting the nominal values, $\hat{A} = NW$ and $\hat{I}_E = 4.255 \times 10^{-4} \text{kg} \cdot \text{m}^2$ into $f(x)$ and $b$. Then, the control input for the exact tracking to overcome the uncertainties is

\begin{equation}
  u = \frac{1}{b} (-\hat{f}(x) - CE(x) - K \cdot \text{sgn}(S))
\end{equation}

where

\begin{equation}
  K = \frac{(1 - \beta_{\text{min}})(\hat{f}(x) + CE(x)) + \alpha + \eta}{\beta_{\text{min}}}
\end{equation}

Since the $\text{sgn}$ function introduces chattering which is highly undesirable for human uses, $\text{sat}$ function with appropriate boundary layers is used instead of $\text{sgn}$ function in the experiments. The value of the boundary was manually determined considering both discomfort feeling caused by the chattering phenomenon and the tracking performance [9].

### 4.3.4 Performance Verification by Experiments

The performance of the proposed algorithms has been verified by experiments with the cRSEA. In the experiments, the cRSEA was installed at the knee joint of a lower extremity orthosis, and various scenarios that could cause an impact to the human joint were tested. In the following experiments, $H$ in (4.35) was set to various values to show the effect of $H$, and $E_{\text{max}}$ in (4.36) was set 4 rad which was about 7.2 Nm. Figs. 4.14 and 4.15 show step responses of the cRSEA using the proposed control algorithms. Since the step input with a big magnitude generates an impact, the step inputs were used for the experiment. In the experiment, the orthosis was mechanically fixed such that the performance of the proposed controller was not affected by the human motions such as a human joint angle and joint torque. Fig. 4.14 shows the safe trajectory generated by the proxy and the actually generated assistive torque controlled by the sliding mode controller. As shown in the figure, the torque error between the proxy torque and the generated torque was small. Fig. 4.15 shows the actual torque generation with different $H$. As shown in the figure, the rate of the assistive torque can be easily changed by the single parameter $H$, and the rate becomes
Figure 4.14: The proxy trajectory and torque error between the proxy torque and the generated torque for $H = 0.1$ (no motions in the human joint).

Figure 4.15: Step responses with different $H$ (no motions in the human joint).
Figure 4.16: Power cut experiments (control input, $u$, is zero for $1.5 \sim 2.5$ sec) with different $H$ (no motions in the human joint).

slow as $H$ increases. The fast change of the assistive torque shown in Figs. 4.14 and 4.15 is not usually used for the desired torque trajectory from the rehabilitation algorithm since it may injure the human joint. However, such dangerous trajectories may be generated by unexpected situations, e.g., a power cut. During the power cut, the spring deflection is not controlled at all since the motor is not controlled. If the spring deflection is very different from the desired spring deflection right after the system is recovered from the power cut, then an impactive large torque may be applied to the human joint in a short period. Power cut situations were simulated in the experiments, and the results are shown in Fig. 4.16. In the experiment, the orthosis was also mechanically fixed, and the control input of the motor was set to zero intentionally for $1.5 \sim 2.5$ sec as if the motor was not controlled by the power cut. Since the generated torque at $2.5$ sec was significantly different from the desired torque, the impactive torque about $2.5$ Nm was applied at $2.5$ sec, which is similar to the step input in Figs. 4.14 and 4.15. As shown in the figure, the rate of the applied torque can easily be changed by different $H$ values. Note that the generated torques with different $H$ are almost the same except the recovering period from the power cut. The robustness of the proposed control algorithm has been tested with actual human motions. In the experiment, the human joint moved arbitrarily, and the desired assistive torque was set to sinusoidal wave with a magnitude of $2$ Nm and a frequency of $0.3$ Hz. To generate the desired torque, the motor angle was controlled to have the desired spring deflection from the arbitrarily changed human joint angle. Fig. 4.17 shows the experimental result with $H = 0.1$, and as shown in the figure, the desired assistive torque was
generated accurately even while interacting with the human motions. The power cut situation was also tested with human motions, and the result is shown in Fig. 4.18. The human joint moved arbitrarily, and the control input of the motor was set to zero for 1.5 ∼ 2.5 sec intentionally. During the power cut, the human joint kept moving, while the motor was not moved at all. As shown in Fig. 4.18, the currently generated torque at 2.5 sec was different with the desired joint torque, the impactive torque of 5 Nm was applied to the human joint at 2.5 sec. But the impact was not directly applied to the human joint since the proxy limited the rate of the assistive torque. As shown in the figure, after power is resumed, the large desired torque at 2.5 sec is slowly applied and the desired assistive torque is accurately generated by the proposed algorithms interacting with human motions.

4.4 A Cable Tension Controller for a Cable-Driven Assistive System

The assistive systems discussed in the previous chapters, a rotary series elastic actuator (RSEA) and a compact rotary series elastic actuator (cRSEA) accounts for the requirements for assistive systems such as precise torque generation, low output impedance and so on. In the assistive systems, the inertia, damping, and friction of the geared motor were effectively rejected by precisely controlling the spring deflection. In spite that the impedance of the motor could be reduced re-
Figure 4.18: Performance of the controller with a power cut (control input, $u$, is zero for $1.5 \sim 2.5$ sec) for $H=0.1$ (arbitrary motions in the human joint).

Remarkably, however, the mass of the actuators could not be rejected and was imposed to the human body when attached to the human.

Previously, a cable-driven system was introduced as an alternative actuation method for human assistive or rehabilitation systems [7, 65]. In this system, actuators are removed from the human body, and the assistive force is transmitted to the human joint through cables. The proposed system consists of two RSEAs, flexible tubes that guide cables, and a set of a pulley and a spring at the end-effector. Each RSEA enables precise force mode control of the cable tension. The flexible tubes enable humans to freely move while being assisted by motor power transmitted by the cables.

To realize the force mode control of the proposed cable driven system, it is a challenge to account for the variable friction in the flexible tubes, as well as the friction and inertia of the actuator (i.e., the geared motor). To generate the desired torque precisely, a hierarchical control strategy is adopted, which consists of a lower level controller and a higher level controller. At the lower level of the control algorithm, each RSEA is controlled to generate precise cable tension. A simple PD controller with a feedforward compensator is applied to this level. For the lower level controller, two accelerometers are installed on the reel of each RSEA, and the angular velocity and position are estimated by a kinematic Kalman filter (KKF) [65]. In this chapter, the higher level controller, which determines the desired cable tension for each RSEA based on the measurements at the end-effector, is discussed. The desired cable tensions are basically determined by the given desired joint torque. For precise transmission of torque, however, the cables should always be...
maintained with proper tensions, which require the compensation of the varying cable friction. For the cables to be appropriately tensioned at all time, a bias is applied to the value of the desired cable tension. Also, since the flexible tubes introduce an uncertain and time-varying friction into the system as their curvature is changed, the cable friction is compensated by feeding back the estimated cable friction in real-time. By the proposed control methods, the proposed cable-driven system realizes a precise force-mode actuation.

4.4.1 System Configuration

Hardware Setup

The main idea of this system is to separate the actuators from a human body. The assistive joint torque for rehabilitation is transmitted to a human body by cable tensions. The proposed system consists of an actuator module, an end-effector, and cables in flexible tubes which connect the two parts.

In the actuator module shown in Fig. 4.19(a), two rotary series elastic actuators (RSEAs) [(a), (c), and (e) in Fig. 4.19(a)] are utilized to apply tension to the cables. Since the cables can only be tensioned, two RSEAs are installed to generate the assistive joint torque in both directions. Also the use of two RSEAs makes it easy to compensate for the change of cable length, which are resulted from the change of curvature of the flexible tubes. Encoders and accelerometers installed on the reel [(f) in Fig. 4.19(a)] are used to measure angles and angular accelerations and to estimate angular velocities in the low level controller [65]. The generated torques are transmitted by the cables in the flexible tubes [(d) in Fig. 4.19(a)]. The end-effector, which is to be attached on a human joint, is shown in Fig. 4.19(b). The pulley [(b) in Fig. 4.19(b)] is wound by cables connected to the actuator module, and it is rotated by the cable tensions. The spring [(a) in Fig. 4.19(b)] installed between the pulley and the human joint measures the transmitted joint torque. Two encoders [(c) and (e) in Fig. 4.19(b)] are applied to measure the angles of the human joint and the pulley. The actuator part and the end-effector part are connected by the cables in flexible tubes [(d) in Figs. 4.19(a) and 4.19(b)] for transmitting torque. The flexible tubes are easily bent such that enough degree-of-freedom is guaranteed in the human joint.

Design of a Hierarchical Controller

The goal of the proposed cable-driven system is to precisely generate desired torque at the end-effector by pulling cables with two RSEAs. The use of cables and flexible tubes allows the users to move freely without carrying the actuators, but it sets a challenge on the precise generation of the desired torque due to the varying cable friction. Note that the friction between the cables and the flexible tubes is related to the cable tension and the curvature of the flexible tube. Since the curvature of the flexible tube is not measured, the cable friction is unknown and time-varying. Also, both of cables should always be tensioned properly for the precise transmission of generated torque.


Figure 4.19: Hardware setup of the cable-driven assistive device.

Figure 4.20: Overall block diagram of the hierarchical controller.
CHAPTER 4. CONTROL OF ASSISTIVE SYSTEMS FOR REHABILITATION

To generate the desired torque precisely in spite of the stated challenges, the whole system is controlled by a hierarchical control strategy. The overall structure of the control algorithm is shown in Fig. 4.20. Detailed explanations about the notions in the figure follow. The hierarchical controller consists of two main controllers; a high level controller [(a) in Fig. 4.20] and a low level controller [(d) in Fig. 4.20]. In the high level controller, the amount of assistive torque is determined by appropriate rehabilitation algorithm [(b) in Fig. 4.20]. Also, based on the determined desired assistive torque, required cable tensions for the upper and the lower RSEAs are calculated by the cable tension controller [(c) in Fig. 4.20]. The desired cable tensions should consider the friction between the cables and the flexible tubes as well as a bias to prevent the looseness of cables. In the low level controller, the desired cable tensions which are determined in the high level controller are achieved [(d) in Fig. 4.20]. The low level controller is proposed in [65], and it is assumed that the desired cable tensions are perfectly generated by the low level controller.

4.4.2 Design of a Cable Tension Controller

Modification of the Desired Assistive Torque

This section describes the cable tension controller [(c) in Fig. 4.20]. The desired assistive torque, $\tau_{Ad}$, is generated at the end-effector by the spring deflection installed between the pulley and the human joint in the end-effector as in (4.56). The spring deflection is made by the position of the pulley which is rotated by the cable tensions from the actuator modules.

$$\tau_{Ad} = k(\theta_{pd} - \theta_H) \quad (4.56)$$

where $k$ is the spring constant, and $\theta_H$ is the human joint angle. Thus, the desired pulley angle, $\theta_{pd}$, is determined as follows.

$$\theta_{pd} = \frac{\tau_{Ad}}{k} + \theta_H \quad (4.57)$$

To have the pulley follow the desired pulley angle, a PI (proportional-integral) controller is applied. The reason why a derivative is not used is the derivative of the tracking error, $E = \theta_{pd} - \theta_p$, is due to noise resulted from the quantization error of the encoder signals. The tracking error can be reformulated as follows.

$$E = \theta_{pd} - \theta_p \quad (4.58)$$

$$= \frac{\tau_{Ad}}{k} + (\theta_H - \theta_p) \quad (4.59)$$

$$= E_{assist} + E_{track} \quad (4.60)$$

where $E_{assist} = \frac{\tau_{Ad}}{k}$ and $E_{track} = \theta_H - \theta_p$. $E_{assist}$ represents the required spring deflection for the generation of the desired assistive torque, and $E_{track}$ means the tracking error of the pulley to track the human joint. Note that if the desired torque is zero, i.e., $\tau_{Ad} = 0$, then $E_{assist}$ is zero, which means that the pulley just follow the human joint without making any spring deflections. As a result of the PI controller, modified desired assistive torque, $\tau_{Ad^*}$, is calculated, which includes the
desired assistive torque from a rehabilitation algorithm as well as the required torque for tracking of the human joint.

**Generation of the Desired Cable Tensions**

Given the modified desired assistive torque, the actual torque is generated by two RSEAs in the actuator module. Since the generated torque is transmitted by pulling the cables, the cable tensions should be controlled precisely. The desired assistive torque is expressed by two cable tensions as (4.61).

\[
\tau^*_{Ad} = r_P (f^u_d - f^l_d)
\]  

where \( r_P \) is the radius of the pulley, and \( f^u_d \) and \( f^l_d \) are the desired tensions of the upper and the lower cable, respectively.

Since the cables can only be tensioned, \( f^u_d \) and \( f^l_d \) can have only positive values. Therefore, if \( \tau^*_{Ad} \) is positive, then \( f^u_d \) is set to a certain positive value and \( f^l_d \) is set to zero. If \( \tau^*_{Ad} \) is negative, then \( f^l_d \) is set to a certain positive value and \( f^u_d \) is set to zero as in (4.62) and (4.63).

\[
f^u_d = \begin{cases} 
\tau^*_{Ad}/r_P & \text{if } \tau^*_{Ad} > 0 \\
0 & \text{otherwise}
\end{cases} \]  

(4.62)

\[
f^l_d = \begin{cases} 
\tau^*_{Ad}/r_P & \text{if } \tau^*_{Ad} < 0 \\
0 & \text{otherwise}
\end{cases} \]  

(4.63)

However, if the desired tension is set to zero, the cable is loosened, which makes the precise torque transmission difficult. Moreover, the varying cable friction that depends on the curvature of the flexible tubes obstructs the precise generation of the desired torque. Thus, two more factors should be considered for the precise transmission of assistive torque; maintaining proper cable tensions and compensating the varying cable friction.

To avoid looseness of the cables even when the desired cable tension is set to zero in (4.62) and (4.63), a bias is introduced to the desired cable tension. By applying the bias to the value of the desired cable tension, the cables can always be properly tensioned so that the generated torque can be transmitted without loss. The value for the bias, \( b \), is set to 10 N in experiments.

Another factor to be considered in the cable tension controller is the compensation of the varying cable friction. Although the proposed system releases users from the burden of the weight of actuators by utilizing cables, it is a challenge to deal with the cable friction, which varies with respect to the curvature of the tube. As shown in Fig. 4.21b, the normal force \((f_N)\) between the cable and the flexible tube is changed as the location of the end-effector is changed from ① to ④ of Fig. 4.21a, i.e., as the curvature of the flexible tube is changed. In ① of Fig. 4.21b, \( f_N \) is close to zero, since the normal force between the cable and the flexible tube is negligible. As the curvature of the tube is increased from ① to ④ of Fig. 4.21b, the magnitude of \( f_N \) is increased, which results in the increase of the cable friction. If the varying friction is not compensated, then some of the generated torque is resisted during transmission, which leads to inaccurate transmission of the generated torque.
The Actuator Module

The End-Effector

The End-Effector

The End-Effector

(a) Change of cable curvature

(b) Change of perpendicular force

Figure 4.21: Change of cable friction.
The cable friction varies according to the curvature of the tube, but it is not easy nor advantageous to measure the curvature of the flexible tubes or $f_N$ directly since it may require complicated sensor sets and the friction depends on many other factors. The varying cable friction is compensated by estimating the cable friction and feeding it back to the cable tension controller in real-time. The cable friction can be estimated with the assumption that all the difference between the generated force in the actuator and the transmitted force in the end-effector is caused by the cable friction. The generated force in the actuator part, $f_{gen}$, is estimated by,

$$f_{gen} = (f^u - f^l)$$  \hspace{1cm} (4.64)

where $f^u$ and $f^l$ are the upper and the lower cable tensions. The actual cable tensions, $f^u$ and $f^l$, are estimated by the generated torque in each RSEA divided by the radius of the reel. The transmitted cable force, $f_{tran}$, is calculated from the measured torque in the end-effector, i.e.,

$$f_{tran} = \frac{\tau_A}{r_P}$$  \hspace{1cm} (4.65)

where $\tau_A$ is the measured assistive torque in the end-effector by the spring. Thus, the cable friction, $f_{cf}$, can be estimated from (4.64) and (4.65) as follows.

$$f_{cf} = f_{gen} - f_{tran}$$  \hspace{1cm} (4.66)

Figure 4.22 shows that the required cable tensions are increased for the same motion as the curvature of the tube is increased. The notions of ① to ④ in the figure correspond to those in Fig. 4.21. In this experiment, the desired trajectory of the pulley is given as a sinusoidal wave, and the location of the end-effector is changed from ① to ④ in Fig. 4.21a to make a curve of the tube. The human side of the end-effector is not constrained, thus the measured torque in the end-effector is zero. The cable friction by (4.66) is shown in Fig. 4.23. As shown in the figure, the cable friction is increased as the curvature of the tube is increased.

The varying cable friction is compensated by feeding back the estimated cable friction to the cable tension controller in real time. Thus, the desired tensions ($f_{d}^{u*}$ and $f_{d}^{l*}$) are sum of the desired tension determined from a given desired assistive torque ($f_{d}^{u}$ and $f_{d}^{l}$ in (4.62) and (4.63)), the bias ($b$), and the term for the cable friction compensation ($f_{cf}$), as follows.

$$f_{d}^{u*} = \begin{cases} \frac{\tau_{Ad}^*}{r_P} + b + f_{cf} & \text{if } \tau_{Ad}^* > 0 \\ b & \text{otherwise} \end{cases}$$  \hspace{1cm} (4.67)

$$f_{d}^{l*} = \begin{cases} \frac{\tau_{Ad}^*}{r_P} + b + f_{cf} & \text{if } \tau_{Ad}^* < 0 \\ b & \text{otherwise} \end{cases}$$  \hspace{1cm} (4.68)

### 4.4.3 Performance Verification by Experiments

The performance of the proposed cable tension controller is verified by experiments. In this experiment, the desired assistive torque is set to zero, and the bias is set to 10 N. For the safety of
Figure 4.22: Estimated cable tensions.

Figure 4.23: Estimated cable friction.
the system, i.e., not to make the cable be cut, the cable friction is compensated by 50% of the estimated cable friction. The location of the end-effector is changed smoothly from ① to ④ in Fig. 4.21a while rotating the human joint arbitrarily. Without friction compensation, there is a resistive torque which is increased as the curvature of the flexible tube is increased as shown in Fig. 4.24. The resistive torque obstructs the precise transmission of the generated torque. With the friction compensation, the resistive torque is reduced to about 50% of the previous case as shown in Fig. 4.25.

4.5 Summary

In this chapter, a series of assistive systems and control algorithms were discussed. For the precise generation of the desired assistive torque, the nonlinear control algorithms were discussed for a rotary series elastic actuator (RSEA) while overcoming the nonlinear resistive torque and modeling uncertainty. To guarantee the robustness for modeling uncertainties, sliding mode control was applied, but it introduced chattering, which was not desirable for physical human-robot interaction. Thus smoothed sliding mode control by utilizing a boundary layer was applied. The RSEA was installed on the knee joint on an orthosis, and the thickness of the boundary layer was varied for the swing and stance phases to decrease the torque error without the chattering phenomenon. The experimental results verified the advantage of the sliding mode control with the varying boundary
To prevent impacts of rehabilitation systems, control algorithms utilizing a proxy have been introduced. The proxy was utilized as a safety buffer between the desired position and current position of the actuator in the rehabilitation system, and the rate of the assistive torque was adjusted by the proxy. The amount of the assistive torque was regulated by limiting the maximum spring deflection. The actual actuator follows the proxy as accurate as possible by a sliding mode controller to compensate for the modeling uncertainties and nonlinearities in the actuator. The performance of the proposed algorithms has been verified by experiments with a compact rotary series actuator (cRSEA) installed on the knee joint of a lower extremity orthosis.

To remove the weight of the actuator in the assistive systems, a cable driven assistive system was previously proposed. Since the end-effector and the actuators were connected by cables in flexible tubes, the humans were allowed to freely move in a certain range while being assisted. To control the cable driven assistive system in a force mode, a hierarchical control strategy was applied. In this chapter, a high level controller of the hierarchical scheme to maintain cable tensions of the cable-driven human assistive system was discussed. Control issues included friction compensation.

Figure 4.25: Performance of the cable tension controller with friction compensation.
Chapter 5

Implementation of Rehabilitation Algorithms

5.1 Introduction

Many models have been proposed to represent the motion control system in a human body. Among the models, the closed-loop control system in Fig. 5.1 is one of the most dominant [107]. The ‘Desired Human Motion’ in the figure, is generated by an external stimulus or an internally self-generated intention. ‘Brain’ in the figure acts as a controller for the motor control, and it consists of motor cortex, cerebellum, basal ganglia, spinal cord, and so on. The muscle control signals (① in Fig. 5.1) generated by ‘Brain’ are transferred to ‘Muscle’ through motor neurons, and ‘Muscle’ moves ‘Body’ via appropriate muscular forces (② in Fig. 5.1). ‘Muscle’ is considered as an actuator, and ‘Body’ represents the musculoskeletal part of a human body, which is a plant to be controlled. The human motions are sensed by various ‘Sensory Organs’ such as eyes, muscle spindles and Golgi tendon organs, and the sensed motions are compared with the desired motions to achieve precise motions. In this chapter, the closed-loop motion control system in Fig. 5.1 is used to analyze human motions and design rehabilitation strategies, and ‘ Desired Human Motion’ in Fig. 5.1 is assumed to be given by the motion planning part of the brain.

Figure 5.1: Closed-loop motion control system in a human body.
While there is a long list of gait disorders which impairs patients’ ability to walk, the causes of the gait disorders can be classified into two big categories: degeneration in muscular systems and that in nerve systems. If the patient has weakened muscles due to accidents, diseases, or aging, then he/she cannot generate enough joint torque to achieve the desired gait motion. For these patients, physical therapists apply appropriate resistive force to muscles to recover the muscular force. Weight training for specific muscles may be one example of possible rehabilitation strategies. This gait rehabilitation strategy was mimicked by the robotic gait rehabilitation device for strengthening muscles [37]. If the muscles are too damaged to recover the original function, then power augmentation systems [48, 56, 122] may help the patients to achieve the normal walking motions.

As shown in Fig. 5.2, if the muscles are too damaged to recover the original function, the difference between the normal joint torque and patient’s joint torque can be added to achieve the normal motions. Thus, joint torques of the lower extremity are useful information to determine desired joint torques for the power augmentation method. In this chapter, an estimation method for observing the joint torques of the lower extremity is discussed. The proposed method is based on the inverse dynamics of a human body, where the human body model applies a planar link-segment model which consists of seven segments. Lagrangian mechanics is applied to calculate the joint torque, and the required motion information is measured by sensors or estimated by kinematic Kalman filter (KKF). The joint torque equation depends on the ground contact conditions of the human body model, and the ground contact conditions can be identified by gait phases. Thus, multiple set of equations are used for the estimation of the joint torques in different gait phases. The gait phases are detected by Smart Shoes, and the detected gait phases are also used for smoothing the joint torques when the ground contact conditions are changed.

The problem of the patients with impaired control by spinal cord injury (SCI) or stroke, is that they cannot control their muscle properly. Assuming that only their nerve systems are degenerated,
CHAPTER 5. IMPLEMENTATION OF REHABILITATION ALGORITHMS

Figure 5.3: Voice/force feedback in gait rehabilitation training.

i.e. their muscles are strong enough to achieve the gait motions, they need to practice and memorize the normal gait patterns by repetitive exercises. For these patients, the physical therapists let the patients exercise the normal gait patterns by applying voice or force feedback as shown in Fig. 5.3. During the gait rehabilitation training, physical therapists keep talking to patients about how they should move to achieve the normal gait patterns, e.g. bending knee more or pushing heel more. Also physical therapists applies assistive torque to the joints to let them recognize that their gait motions deviate from the normal gait, and to guide them to the normal gait trajectory.

By mimicking these functions of physical therapists, robotic gait rehabilitation systems which utilize visual feedback [4, 8, 73] or assistive torque were devised [30, 43, 44]. Since the assistive torque let the patient practice the normal gait pattern easily and effectively, it is one of the most important factors in the robotic gait rehabilitation systems to determine the amount of the required torque for the patient. The assistive torque should be proportional to the deviated angle from the normal gait trajectory for patients to have the “feeling” about the normal gait trajectory. Also the joint should be guided accurately to the normal gait trajectory by the assistive torque. Figure 5.4 shows this rehabilitation method to practice the normal gait trajectory.

In this chapter, a rehabilitation strategy which imposes an imaginary potential field around the desired trajectory is introduced. In this strategy, the induced force by the potential field compels the joint to be moved to the normal joint trajectory if the joint position deviates from the normal joint trajectory. The rehabilitation strategy by the potential field provides an effective method to calculate the required torque for patients to practice the normal gait trajectory. However, the joint can be guided to the desired trajectory more accurately by utilizing the cyclic and repetitive characteristic of gait motions. Thus, the gait rehabilitation strategy inspired by an iterative learning algorithm is proposed. The proposed rehabilitation strategy utilizes one stride advanced error and error derivative to calculate the assistive torque in the current stride. By using the information in the previous strides, repetitive abnormal gait patterns can be penalized more by stronger assistive torque. The performance of the proposed gait rehabilitation strategy was verified by simulations.
5.2 Estimation of Lower Extremity Joint Torques in Normal Gait

Human motions are achieved by the movement of a muscular-skeletal system. To achieve the desired motion, skeletal muscles, or voluntary muscles, which are anchored by tendons to the skeletal system, contract to generate appropriate force. Multiple muscles are involved in the movement of one joint. Muscular forces acting on one joint result in a resultant joint torque, which is actual torque that makes the joint motion. Thus, observing the joint torque helps deep understanding about human motions, and the information about the joint torque can be utilized in many fields.

Information on the joint torques of the lower extremity can also be utilized for diagnosis and treatment of patients suffering from gait disorders. By observing the joint torque, physical therapists can diagnose which joint does not generate enough torque, then they can focus on the muscles related with the joint. For gait assistive systems, the information about the joint torques of the lower extremity can be utilized. To determine the amount of required assistive joint torques, the desired joint torque to achieve the desired motion and the currently generated joint torque are necessary.

One of the conventional methods to observe the joint torque of the lower extremity is a camera-based method represented by [119]. In this method, several optical markers are mounted on a human body and cameras capture the reflected light from the markers. It produces well-quantified and accurate results on the joint torques of the lower extremity. However, it has several drawbacks such as 1) it requires cumbersome equipment 2) it can be performed only in a laboratory, and 3) the joint torque data is produced after the experiment, i.e., not in real-time. Another method to observe the joint torques is using bio-sensors such as an electromyography (EMG) sensor. Some
researchers have applied EMG sensors to an exoskeleton-type power augmentation system [48]. One of the drawbacks of the EMG sensors is its sensitivity, i.e., the EMG signal is easily affected by environmental conditions. In this chapter, an estimation method for the joint torques of the lower extremity by the inverse dynamics of a human body is proposed to overcome the above drawbacks of previous methods.

For the inverse dynamics of a human body, a dynamic model of a human body is required. In this chapter, a planar link-segment model which consists of seven segments is proposed. The model includes six joints: two each at hips, knees, and ankles. The utilized model is appropriate to explain the walking motion since walking is a sagittal directional motion and main joint torques which propel the walking motion are in the sagittal plane. Also seven segments, one for HAT (head, arm, and trunk) and three for each leg (thigh, shank, and foot), is a good compromise between complexity and accuracy of the representation of the actual human body for gait analysis. Based on the proposed human model, Lagrangian mechanics is applied to calculate the joint torques. The anthropometric data required in the inverse dynamics equation are obtained from anthropometric database or equations [40, 121]. Motion information such as the joint angles and the joint angular accelerations are measured by sensors (e.g. encoders) and joint angular velocities are estimated by a kinematic Kalman filter (KKF).

One of the drawbacks of this method is that the joint torque equations are dependent on the ground contact conditions of the human model, i.e., whether the human body is supported by a single leg or both legs, which parts of feet touch the ground, and so on. Different equations for the joint torque may result in the discontinuity of the joint torques when the ground contact conditions are changed. For smooth transitions of the joint torques, gait phases obtained by Smart Shoes are used.

5.2.1 A Human Body Model

For gait analysis, the human body is often modeled as a link-segment system. However, since ground contact conditions are changed during walking, the joint torques can not be calculated by only one equation. In this chapter, the different ground contact conditions with gait phases and a link-segment human model are discussed.

Different Ground Contact Conditions with Gait Phases

Since walking is a cyclic motion, the walking motion of each stride is represented as a gait cycle as introduced in Chapter 2. Characteristics of the ground contact conditions of each gait phase are briefly summarized below.

Initial Contact (IC): Initial contact phase is the beginning of the gait cycle. This phase is frequently called ‘heel strike’, since there is a distinct impact between the heel and the ground in normal gait.

Loading Response (LR): The loading response is the double support period between an initial contact event and an opposite toe off event. During this period, the foot is lowered to the ground
by plantarflexion. In this phase, the forefoot part starts to contact the ground.

**Mid-Stance (MS):** Mid-stance is the period of the gait cycle between an opposite toe off event and a heel rise event. In mid-stance phase, the whole parts of the foot touch the ground.

**Terminal Stance (TS):** Terminal stance is started from a heel off event. Thus the ground contact force at heel starts to decrease.

**Pre-Swing (PS):** The Pre-Swing is the last motion phase of stance. In this phase, only toe part touches the ground.

**Swing Phases (SW: Initial Swing, Mid-Swing, and Terminal Swing):** Toe off separates swing phases and stance phases. During swing phases, the foot does not touch the ground until next initial contact phase.

Figure 5.5 shows the different limb supports according to the eight gait phases. As shown Fig. 5.5, gait phases can be divided into two categories: single limb support phases and double limbs support phases. In single limb support phases which includes MS, TS and swing phases, one leg supports the human body and the other leg swings. In double limbs support phases which includes IC, LR, and PS, the human body is supported by both legs: one leg touches the ground with the forefoot and the other leg touches the ground with the heel. These different ground contact conditions, i.e., whether the body is supported by a single limb or double limbs, and which part of the foot touches the ground, result in different equations for the estimation of the joint torques.

Since the ground contact conditions are different according to gait phases, the information on
A Link-Segment Model of the Human Body

The human model used in this chapter is a link-segment model which consists of seven segments in the sagittal plane. The model includes six joints: two each at hips, knees, and ankles. Since the human body has a large number of the degrees of freedom, a link-segment model for the human body needs many segments and joints to represent the actual human body. An excessive number of segments, however, increases the complexity of the resulting joint torque equations because of the complex coupling among all the segments; on the other hand a too small number of segments reduces the accuracy of the model. Thus, the seven segments, one for HAT (head, arm and trunk) and three for each leg (thigh, shank, and foot), is a good compromise between complexity and accuracy for the representation of the actual human body. Also, even though the proposed model is planar on the sagittal plane, most of the gait motions can be explained with this model since the main walking motions happen in the sagittal plane. Fig. 5.6(a) shows the proposed human model, and Fig. 5.6(b) shows the notations and the directions of joint torques used in this chapter. The global reference system (GRS) and the sign convention of the model are shown in the figure. The capital letters means the length of the part shown in the figure. A foot is modeled as a triangular shape to represent the actual foot shape.

As stated earlier, the ground contact conditions are changed according to gait phases. The dif-
different ground contact conditions result in different constraints of the human model. For example, the pivot point which means a fixed point in the model is changed with the ground contact conditions. It is the heel in IC, but is the hallux in PS. From this pivot point, the position and the velocity of each segment are calculated. In swing phases, the hip joint is used as a pivot point, and its accelerations in \( x \) and \( y \) directions of GRS are measured. Fig. 5.7 shows the four ground contact conditions of the swinging leg, the supporting leg with whole foot, the supporting leg with forefoot, and the supporting leg with heel. These different constraints of the model introduce multiple sets of equations for estimation of the joint torques. Thus, the joint torques of SW (\( \hat{\tau}_{SW} \)), MS, TS (\( \hat{\tau}_{MS}, \hat{\tau}_{TS} \)), PS (\( \hat{\tau}_{PS} \)), and IC, LR (\( \hat{\tau}_{IC}, \hat{\tau}_{LR} \)) are calculated by the dynamics equations obtained by the models in Fig. 5.7 (a), (b), (c), and (d).

Due to the multiple set of joint torque equations, there may be discontinuity in the calculated joint torques when the ground contact conditions are changed. Such discontinuities are smoothed by the gait phases detected by Smart Shoes as follows. The detected gait phase, \( \mu_i \), are set as the weighting vector, i.e., (5.1).

\[
W = [\mu_{IC} \ \mu_{LR} \ \mu_{MS} \ \mu_{TS} \ \mu_{PS} \ \mu_{SW}]^T \in \mathbb{R}^{6 \times 1} \quad (5.1)
\]

where \( \mu_{IC} + \mu_{LR} + \mu_{MS} + \mu_{TS} + \mu_{PS} + \mu_{SW} = 1 \). The joint torques are calculated based on the human model with corresponding constraint as follows.

\[
\Gamma = [\hat{\tau}_{IC} \ \hat{\tau}_{LR} \ \hat{\tau}_{MS} \ \hat{\tau}_{TS} \ \hat{\tau}_{PS} \ \hat{\tau}_{SW}] \in \mathbb{R}^{1 \times 6} \quad (5.2)
\]

Then the smoothed joint torque is obtained as (5.3).

\[
\hat{\tau}_{Joint} = \Gamma W \quad (5.3)
\]

### 5.2.2 Estimation of Lower Extremity Joint Torques

#### Analysis with Lagrangian Mechanics

For the estimation of the joint torques with the proposed human model, Lagrangian mechanics is applied. A general Lagrangian equation in vector form is

\[
\frac{d}{dt} \frac{\delta(W + T)}{\delta \dot{q}} - \frac{\delta(W + T)}{\delta q} = 0 \quad (5.4)
\]

where \( q \) is the generalized coordinate vector, \( T \) is the kinetic energy of the system, and \( W \) is the virtual work done by external forces and torques. The virtual work is the sum of the virtual work done by conservative forces \( (W_c) \) and by non-conservative forces \( (W_{nc}) \), i.e.,

\[
W = W_c + W_{nc} \quad (5.5)
\]

The conservative work can be expressed as the negative of the potential energy of the system \( (V) \), i.e., \( \delta W_c = -\delta V \). Thus,

\[
\delta(W + T) = -\delta V + \delta W_{nc} + \delta T = \delta L + \delta W_{nc} \quad (5.6)
\]
Figure 5.7: Different ground contact conditions.
where \( L = T - V \) is the Lagrangian function. Then (5.4) can be rewritten as follows.

\[
\frac{d}{dt} \frac{\delta L}{\delta \dot{q}} - \frac{\delta L}{\delta q} = \frac{\delta W_{nc}}{\delta q} - \frac{d}{dt} \frac{\delta W_{nc}}{\delta \dot{q}}
\]  

(5.7)

For the details of Lagrangian mechanics, refer [33]. In this model, the distance from GRS to the pivot point (\( X \) in Fig. 5.7) and joint angles of ankle, knee and hip (\( \theta \)'s in Fig. 5.7) are used as the generalized coordinates. Using (5.7), the equations for the joint torques of the lower extremity are derived. For the calculation of the joint torque, ground reaction forces measured by Smart Shoes, anthropometric data and motion information are required.

### Anthropometric Data

To calculate the joint torques using the derived dynamics equations, anthropometric data such as length, mass and moment of inertia of each segment are required. There are huge anthropometric database about human body segments with different height, weight, and age [40]. Also several simple equations show the relationship among anthropometric data [121]. In this chapter, those database and equations are used for obtaining anthropometric data.

### Angle, Angular Velocity, and Angular Acceleration

Motion information such as joint angles, angular velocities and angular accelerations are required to solve the derived joint torque equation. There are several methods to measure each motion information. The joint angle can be measured by an encoder or an angular potentiometer. Since encoders provide noise-free signals except for quantization errors, encoders are used for measurement of the joint angles. The joint angular acceleration can be directly measured by an angular accelerometer, but it is not suitable for the present application due to its size. Instead, an MEMS linear accelerometer is attached on the center of each segment, and the measured linear acceleration is converted to angular acceleration by multiplying the distance between the joint and the center of each segment. The joint angular velocity can be calculated by differentiating the measured joint angle, i.e.,

\[
\omega = \frac{\delta \theta}{T_s}
\]  

(5.8)

where \( T_s \) is the sampling time. To minimize the estimation delay and enlarge the frequency range of the velocity estimate, the sampling rate should be high. However, this makes the estimate noisy due to the quantization error of an encoder. Since both the joint angle and the joint angular acceleration are available from sensors, the angular velocity can be estimated by a kinematic Kalman filter (KKF). KKF uses a kinematic model relating the angle (\( \theta \)) to the angular acceleration (\( \alpha \)) i.e.,

\[
\dot{\theta}(t) = \alpha(t)
\]  

(5.9)

To find a KKF, (5.9) is expressed in state space by taking the acceleration measurement as an input and the angle measurement as an output and including the measurement noises for the angle
and angular acceleration measurements. Namely,
\[
\dot{x}(t) = Ax(t) + B(\alpha(t) + w_\alpha(t)) \tag{5.10}
\]
\[
\theta_M(t) = Cx(t) + v_\theta(t) \tag{5.11}
\]
where \( x = \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix} \), \( A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \), \( B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \), \( C = [1, 0] \), \( w_\alpha \) is the measurement noise for accelerometer measurement and \( v_\theta \) is the measurement noise for angle measurement. Note that the acceleration measurement \( \alpha(t) \) and the actual acceleration \( \ddot{\theta}(t) \) are related by
\[
\alpha(t) = \ddot{\theta}(t) - w_\alpha(t) \tag{5.12}
\]
Since the kinematic equations (5.10) and (5.11) do not depend on physical parameters and external disturbances, they are very well suited for Kalman filter theory.

For discrete time implementation, the system is rewritten as a discrete time form, i.e.,
\[
x(k + 1) = A_k x(k) + B_k (\alpha(k) + w_\alpha(k)) \tag{5.13}
\]
\[
\theta_M(k) = C x(k) + v_\theta(k) \tag{5.14}
\]
where \( k \) is a discrete time index, and \( A_k \) and \( B_k \) are zero-order-hold discrete time equivalents of \( A \) and \( B \), i.e., \( A_k = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \), \( B_k = \begin{bmatrix} \frac{T_s^2}{T_s^2} \\ \frac{T_s}{T_s} \end{bmatrix} \). Then, the KKF is given by
\[
\hat{x}(k + 1) = A_{kc} \hat{x}(k) + B_{kc} (\alpha(k) + w_\alpha(k)) + F \theta_M(k + 1) \tag{5.15}
\]
where \( A_{kc} = (I - FC)A_k \), \( B_{kc} = (I - FC)B_k \), and the KKF gain \( F \) is given by a discrete time algebraic Riccati equation as follows.
\[
F = MC^T [CMC^T + V]^{-1} \tag{5.16}
\]
\[
M = A_k MA_k^T + B_k W B_k^T - A_k M C^T [CMC^T + V]^{-1} C M A_k^T \tag{5.17}
\]
where \( W \) and \( V \) are the variance of input noise \( w_\alpha(k) \) and output noise \( v_\theta(k) \), respectively, and \( M \) is the one-step prediction error covariance matrix. For the details of KKF, see [70], and [53].

5.2.3 Experimental Results

Experimental Setup

A simple linkage shown in Fig. 5.8, which has various sensors on it, has been built to verify the proposed method. It is bent to fit with body shape, and its length is adjustable. Six encoders ((1) in Fig. 5.8(a)) are installed on each joint to measure the corresponding joint angle. An inclinometer and an accelerometer ((2) in Fig. 5.8(a)) are installed on a hip joint to measure the acceleration in \( x \) and \( y \) direction of GRS for the pivot point of swing phases. Linear accelerometers ((3) in Fig. 5.8(a)) are attached to the center of each segment to measure the joint angular acceleration.
(1) Encoder (2500 CPR) S2, US Digital

(2) 2-axis inclinometer (2V/g, V=2sinθ) SCA100T, VTI Tech.
2-axis accelerometer (480mV/g) MMA6271QT, Freescale Inc.

(3) 1-axis accelerometer (1200mV/g) MMA2260D, Freescale Inc.

(a) Sensors on the linkage

(b) Experimental setup on a human body

Figure 5.8: Experimental setup.
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Experimental Results

As discussed earlier, there may be discontinuities in the estimated joint torque when the ground contact conditions are changed. Fig. 5.9 shows zoomed knee and ankle joint torques when the gait phase is changed from MS to swing phases. Sudden changes of the estimated joint torques are observed in Fig. 5.9(b). In this case, the gait phases were detected as discrete events by taking the gait phase with the largest fuzzy membership value. The discontinuity of estimated joint torque is more than 20 Nm in the ankle joint, which does not happen in the actual knee joint. Using the fuzzy membership values of detected gait phases as in (5.3), the estimated joint torque is smoothed as shown Fig. 5.9(c).

Fig. 5.10 shows the estimated hip, knee, and ankle joint torques in the normal gait with the proposed method. The joint torques are normalized with the body weight. In IC and LR, the hip and knee joints generate torques to the extensor direction to propel the body forward. The ankle joint generates its maximum torque in MS and TS for the same reason. In the swing phases, the generated torques are smaller than other phases, which means that the main power source in swing phases are gravitational force, and not human joint torques.
Figure 5.10: Estimated joint torque.
5.3 A Gait Rehabilitation Strategy Inspired by an Iterative Learning Algorithm

In manual gait rehabilitation training, physical therapists try for patients to practice and memorize normal gait patterns by applying assistive torque to the patient’s joint if the patient’s gait deviates from the normal gait. Thus, it is one of the most important factors in the robotic gait rehabilitation devices to determine the amount of assistive torque to practice the normal gait. In this chapter, the gait rehabilitation strategy inspired by a potential field around the desired trajectory and an iterative learning algorithm which uses the cyclic and repetitive characteristic of gait motions are proposed [7, 15]. The simulation results with human models, and experimental results using an active knee orthosis are presented, which verify that the proposed strategy can generate appropriate assistive joint torque to practice the knee motions for the normal gait.

5.3.1 A Gait Rehabilitation Strategy Inspired by a Potential Field

The assistive torque in robotic gait rehabilitation devices provides the “feeling” for patients to sense how far their gait motions are deviating from the normal gait trajectories. By the “feeling”, the patients can learn the normal gait trajectory and be guided to the normal gait trajectory. Thus, the assistive torque should be proportional to the deviation from the normal gait trajectory, and be capable to guide the joint to the exact gait trajectory. Of course, the safety factors, e.g. maximum of torque, should be considered. As the amount of torque is related to the deviated angle from the normal trajectory, it can be considered as the impedance between human and the robotic gait rehabilitation device. Impedance defines the relationship between the manipulator force and the deviation between the desired and actual position [52].

The concept of the induced force by the potential field is shown in Fig. 5.11. In this strategy, an imaginary potential field is put around the desired trajectory, which generates induced forces for the joint to stay on the desired trajectory.

The potential field, $P_A$, for the gait rehabilitation strategy can be expressed as a function of the human joint angle, $y_H$, and the angle of normal gait, $y_N$, as follows.

$$P_A = \alpha(y_H - y_N)^\beta$$  (5.18)

The values of $\alpha$ and $\beta$ can be selected as any values according to the status of patients or the aim of rehabilitation training, as long as $P_A$ has a global minimum at $y_N$. The amount of the assistive torque is calculated as the negative gradient of the potential field with respect to the human joint angle: i.e.

$$\tau_A = -\nabla y_H P_A$$  (5.19)

One example of the proposed potential field is shown in Fig. 5.12. In this figure, the desired human joint angle, $\theta_{Hd}$, is given as a simple sinusoidal wave (a thick line in the figure), and the potential field for rehabilitation (gray lines in the figure) is given as a quadratic function in (5.20)
by selecting $\alpha = 1$ and $\beta = 2$ in (5.18). If the human joint deviates from the desired angle (dots in the figure), then torque in (5.21) is generated by the potential field for the joint to be moved back to the desired position. Note that setting $\beta = 2$ results in proportional control law.

\[ P_A = (y_H - y_N)^2 \]  
\[ \tau_A = -2(y_H - y_N) \]  

5.3.2 A Gait Rehabilitation Strategy Inspired by an Iterative Learning Algorithm

The rehabilitation strategy by the potential field provides an effective method to calculate the required torque for patients to practice the normal gait trajectory. However, the joint can be guided to the desired trajectory more accurately by utilizing the fact that walking motions are repeated over strides.

It is not difficult to observe that the abnormal gait motions are cyclic and repetitive as the normal gait motions. Figure 5.13 shows normal and abnormal knee joint angles in three strides by the experiment in Section 5.3.5. As shown in the figure, the abnormal knee motions are repeated over strides as the normal motions are. Note that the angle deviations from the normal knee angles in one stride are similar with those in the previous strides. In order to generate appropriate assistive
Figure 5.12: Example of a potential field.
torques in the repeated strides, an iterative learning algorithm is applied. In this algorithm, the amount of assistive torque in a current stride is calculated based on that in the previous strides.

Many applications utilizing the iterative learning control (ILC) can be found in controls of mechanical systems for repeated tasks such as industrial robotics [117], wafer stage systems [79], computer-numerical control tools [57], injection molding systems [47], and so on. ILC is based on the paradigm of learning as the name suggests. In a repetitive process, information from earlier iterations can be used to improve performance in the current iteration. ILC is anticipatory and can compensate for exogenous signals, such as repeating disturbances, in advance by learning from previous iterations [23]. Also the design method requires minimal model information about the plant being controlled [78].

A widely used ILC control input is

\[ u_{k+1}(j) = Q(q)[u_k(j) + L(q)e_k(j + 1)] \]  

where \( j \) is the time index, \( k \) is the iteration index, \( q \) is the forward time-shift operator, \( qx(j) \equiv x(j + 1) \). \( Q(q) \) and \( L(q) \) are a \( Q \)-filter for enhanced stability and a learning function, respectively. A block diagram with a plant \( P \) and the control input (5.22) is drawn in Fig. 5.14. Subscript \( k \) represents signals in \( k^{th} \) iteration. The errors and the control inputs in previous iterations are saved in memory, and used to calculate the control input in the current iteration.
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By combining the iterative learning algorithm in (5.22) with the potential field algorithm in (5.19), the following gait rehabilitation strategy is proposed to calculate the assistive torque.

\[
\tau_{A,k+1}(j) = f(e_{k+1}(j)) + Q(q)[\tau_{A,k}(j)
+ \alpha_p e_k(j+1) + \alpha_D \left\{ \frac{e_k(j+1) - e_k(j)}{T_s} \right\}]
\]  

(5.23)

where \( e_k(j) = y_N(j) - y_{H,k}(j) \). \( y_N \) is the normal trajectory and \( y_{H,k} \) is measured human motion in the \( k^{th} \) stride. The first term in (5.23), \( f(e_{k+1}(j)) \), represents the assistive torque by the potential field algorithm defined in (5.19). If \( \beta \) in (5.18) is not two, then it would be nonlinear with respect to \( f(e_{k+1}(j)) \), but it still only depends on the error in the current stride (① in Fig. 5.15). The remaining terms in (5.23) are by the iterative learning algorithm, i.e, learned from the error and the error derivative of the previous stride (② in Fig. 5.15). The iterative learning algorithm in (5.23) uses PD-type update law to calculate the rehabilitation torque; P-type term uses the error signal, and D-type term uses the error derivative in the previous iteration. By utilizing the one step advanced error signal and error derivative, repetitive abnormal gait motions can be penalized more. If the potential field is selected as a simple quadratic function in (5.20), the rehabilitation
algorithm in (5.23) can be written as

$$\tau_{A,k+1}(j) = K_p e_{k+1}(j) + Q(q)[\tau_{A,k}(j) + L(q) e_k(j+1)]$$

(5.24)

where $K_p$ is from the potential field algorithm, and $L(q) = \alpha_p + \frac{Q\alpha}{T_s}(1 - q^{-1})$. (5.24) can be rewritten as

$$\tau_{A,k+1}(j) = K_p e_{k+1}(j) + w_{k+1}(j)$$

(5.25)

where

$$w_{k+1}(j) = Q(q)[\tau_{A,k}(j) + L(q) e_k(j+1)]$$

(5.26)

Then,

$$w_{k+1}(j) = Q(q)[w_k(j) + (K_p q^{-1} + L(q)) e_k(j+1)]$$

(5.27)

which uses a new learning function as $K_p q^{-1} + L(q)$.

The block diagram of the proposed rehabilitation strategy is depicted in Fig. 5.16. The assistive torque at the $(k+1)^{th}$ stride, $\tau_{A,k+1}$, is added to the human joint torque, $\tau_H$. By the assistive torque, the patient can easily reach the normal gait trajectory, and memorize the motion by repeated exercises. The gait motions are sensed as angles by encoders, and the deviated angles ($e_{k+1}$) from the normal gait motions ($y_N$) are saved in the memory as well as the assistive torque to be used to compute the assistive torque by the iterative learning algorithm.

In frequency domain, the learning filter of the learning algorithm in (5.23) corresponds $L(z) = \alpha_p z + \alpha_D z^{1 - 1}$, where $T_s$ is the sampling time. Since D-type iterative learning update law which uses the error derivative is included in this learning algorithm, $Q$-filter should be designed to remove high frequency components of the error derivative. Since the range of the normal walking motion is up to about 10 Hz [121], the cut-off frequency of $Q$-filter is set to slightly larger than 10Hz as shown Fig. 5.17.

5.3.3 Forgetting Factor and Gait Trajectory Adaptation

Patients’ gait motions may be changed during the gait rehabilitation treatments by adapting the desired trajectory. The algorithms in (5.23) uses all the previous information for the calculation of the current assistive torque. Due to the change in gait motions during the rehabilitation treatment, it is inadequate to use too old history of the assistive torque for the calculation of the current assistive torque. By utilizing the forgetting factor, $\lambda$, as in (5.28), the effect of old assistive torques can be reduced. The forgetting factor has a range between 0 and 1, and it determines how fast the previous assistive torques are forgotten in the calculation of the current assistive torque.

$$\tau_{A,k+1}(j) = C(q) e_{k+1}(j) + Q(q)[\lambda \cdot \tau_{A,k}(j)$$

$$+ \alpha_p e_k(j+1) + \alpha_D \left\{ \frac{e_k(j+1) - e_k(j)}{T_s} \right\} ]$$

(5.28)
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Figure 5.16: Block diagram of the proposed rehabilitation strategy.

Figure 5.17: Design of $Q$-filter.
The normal trajectory may not always be the correct trajectory for patients to follow. In other words, just compelling the patients’ joints to move to the normal trajectory does not always help the patients to be rehabilitated. Thus, in the proposed algorithm, the desired gait trajectories are changed based on the normal trajectories according to the rehabilitation intervention as in (5.29).

\[ y_{\text{new}}(t) = a(t) \cdot y_{\text{normal}} \left( \frac{t}{b(t)} \right) + c(t) \]  

(5.29)

where \( y_{\text{normal}} \) and \( y_{\text{new}} \) represent the normal trajectory and the new trajectory, respectively. The parameter \( a \) scales the amplitude of \( y_{\text{normal}} \), \( b \) stretches the time and influences the period of the motion, and \( c \) changes the offset.

The variations mentioned above help the efficiency of the rehabilitation treatments with the proposed algorithms be improved by allowing sufficient degrees of freedom in the gait rehabilitation strategy. In the following simulations and experiments, \( \lambda \) in (5.28) was set to 1, and \( a, b \) and \( c \) in (5.29) were set to 1, 1 and 0, respectively.

### 5.3.4 Simulation Study

The proposed rehabilitation strategy in (5.23) is simulated with human models. The human body can be modeled with different mathematical complexities according to the number of joints and links \([6, 93]\). Complicated models with many joints and links may give accurate analysis, but an excessive number of segments increases the complexity of the resulting equations because of the complex coupling among all the segments. Thus, two widely-used simple models, a pendulum model and an inverted pendulum model, are used for swing phases and stance phases. In swing phases, the knee joint torque is primarily used for swinging the shank and the foot. This can be simplified by a pendulum as shown in Fig. 5.18(a). The shank and the foot are modeled as a uniform cylinder which has the mass of \( m_1 \) and the length of \( l_1 \). In stance phases, the knee joint torque is used for the upper body advancement. This can be modeled as an inverted pendulum; the foot is fixed on the ground, and the body upper parts above the knee is an inverted pendulum as shown in Fig. 5.18(b). The whole upper body is also modeled as a uniform cylinder which has the mass of \( m_2 \) and the length of \( l_2 \). To obtain the system equation in swing phases, the kinetic and potential energies of the system are computed as follows.

\[ T = \frac{1}{4} m_1 l_1^2 \dot{y}^2 \]  

(5.30)

\[ V = m_1 g l_1 c (1 - \cos y) \]  

(5.31)

where \( T \) and \( V \) represent the kinetic energy and the potential energy, respectively. Then, the system equation is obtained by Lagrangian mechanics as follows.

\[ \tau = \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{y}} \right) - \frac{\partial L}{\partial y} \]  

(5.32)

\[ = \frac{1}{2} m_1 l_1^2 \ddot{y} + m_1 g l_1 c \sin y \]  

(5.33)
where \( L = T - V \). Likewise, the system equation in stance phases is,

\[
\tau = \frac{1}{2} m_2 l_2^2 \ddot{y} - m_2 g l_{2c} \sin y
\]  

The normal knee angle is given by the experiment in Section 5.3.5. ‘Brain’ in Fig. 5.16 is modeled as a poorly tuned PID controller which generates abnormal muscle control signals so that ‘Muscle’ in Fig. 5.16 cannot generate appropriate torque to achieve the normal knee motions. Since ‘Brain’ can control the whole body stably even though the resulting motions are abnormal, and the amount of the assistive torque is smaller than the human torque, stability issues about the proposed rehabilitation strategy are not discussed in this chapter. To prevent discrepancy in the simulated angle when the human models are switched, two models are changed smoothly with appropriate weighting as in [6].

The simulation results by the proposed algorithm in (5.23) are shown in Fig. 5.19. Note that the deviated angle in the first stride is larger than other strides since the first stride is a learning period for the iterative learning algorithm. In other words, only the potential field algorithm is used in the first stride. But once the iterative learning algorithm is started from the second stride, the proposed strategy generates appropriate assistive torque so that the deviated angle from the normal knee angle is decreased.
Figure 5.19: Simulation results.
5.3.5 Experimental Results

Knee Motions in Normal Gait

Since the proposed rehabilitation strategy is applied to the knee joint, the normal knee motions in sagittal plane is studied in this chapter. Also the abnormal knee motions for the experiments are compared with the normal knee motions.

The normal knee motions in one stride is shown in Fig. 5.20 with corresponding gait phases. The normal knee angle is obtained by averaging the data from normal healthy male objects without any known gait disorders, and verified by literatures [96,121]. Since small motions in the knee lead to significant changes in the foot or the whole body, knee mobility and stability are major factors in the normal gait. The knee has three important functions during walking; shock absorption, stance stability, and limb advancement [96]. In stance, shock absorption is necessary when the limb is loaded, and stance stability is important for secure weight bearing. In swing, the limb is advanced by rapid flexion of the knee.

Normal knee angles during walking are within the range of 0° to 70° as shown in Fig. 5.20. At initial contact phase, the knee is flexed about 5°. In loading response phase, putting body weight on the limb instantly disturbs the knee’s stability. The knee flexion, however, provides shock absorption in load response phase. Through the loading phase, the knee is rapidly flexed throughout the loading phase. During the rest of stance, the knee extends and the ankle dorsiflexes for the body mass to be moved forward. In swing, the knee is flexed to lift the foot for limb advancement. This is the critical action that assures foot clearance as the limb swings forward from the trailing posture.

Slightly impaired knee motions mimicked by a healthy person without any known gait disorders were used in the experiments. The healthy subject was asked to wear the experimental setup in Fig. 5.22, and walk on the treadmill at a speed of 3.2 km/h with the abnormal knee motions.
CHAPTER 5. IMPLEMENTATION OF REHABILITATION ALGORITHMS

Figure 5.21: Abnormal knee motions.

shown in Fig. 5.21(a). As shown in the figure, the knee is not fully extended in stance (②∼③ in Fig. 5.21(a)), which results in insufficient forward movement of the upper body. Also the knee is not flexed enough in swing phases (④∼⑤ in Fig. 5.21(a)), as a result, the foot clearance is not enough, i.e., the forefoot is dragged on the floor. The knee angle of the abnormal gait in three strides is shown in Fig. 5.21(b), and the corresponding numbers of abnormal motions in Fig. 5.21(a) are presented in the figure.

Experimental Setup

The proposed gait rehabilitation strategy is applied to the abnormal knee motions in Fig. 5.21. A compact rotary series elastic actuator (cRSEA) discussed in Chapter 4 was used as an experimental setup. It is operated in ideal force/torque mode by compensating the mechanical impedance, which means that it generates the desired torque precisely. Thus, the computed rehabilitation torque, \( \tau_{A,k+1} \) in Fig. 5.16, is assumed to be generated accurately in this experiments.

The cRSEA was installed on the knee joint of an orthosis as shown in Fig. 5.22(a). A subject wore the active knee orthosis as shown in Fig. 5.22(b), and walked on the treadmill at a speed of 3.2 km/h. The walking speed was set slower than normal walking speed since it is easier to practice the normal gait in slower speeds. The normal knee joint angle in Fig. 5.20 was scaled with respect to the walking speed.
Experimental Results

The goal of the experiments is to verify that the proposed strategy generates adequate assistive torque to practice the normal gait so that the abnormal gait motions can be improved to the normal gait motions. As shown in the experimental results in Fig. 5.23a(c), appropriate assistive joint torques were generated by the proposed algorithm. Also, by the generated assistive joint torque, the abnormal knee motions in Fig. 5.21 were changed to the normal knee motions as shown in Fig. 5.23(a) and 5.23(b).

Even though the abnormal gait motions were performed by a healthy person, not a patient, but it was observed that the normal person could not mimic the abnormal walking motion easily, and was guided to the normal knee trajectory by the generated assistive torque. It took some times to adapt to the active knee orthosis and the normal knee trajectory, but after the adaption, the knee could follow the normal gait trajectory by the assistive torque.

5.4 Summary

In this chapter, implementation of rehabilitation algorithms in the assistive systems was discussed. First, an estimation method for the joint torques of the lower extremity by the inverse dynamics was proposed. For the inverse dynamics of a human body, a planar link-segment human model which consists of seven segments were applied. Lagrangian mechanics was utilized for the calculation of the joint torques. Since the ground contact conditions of the human model are changed according to the gait phases, multiple set of equations for the joint torque have been utilized. The gait phases
Figure 5.23: Experimental results.
were detected by Smart Shoes, and the detected gait phases were used for smoothing the estimated joint torques when the ground contact conditions were changed. The required motion quantities were measured from various sensors or estimated by kinematic Kalman filter (KKF). The proposed method was validated by experiments.

Next, the rehabilitation strategy to determine the amount of assistive torque to practice the normal gait in robotic gait rehabilitation devices was discussed. The rehabilitation strategy inspired by an iterative learning scheme was proposed. It utilized the characteristics that motions are repeated over strides. In this algorithm, the amount of the assistive torque was computed based on the information in the previous strides. The performance of the proposed algorithm was verified by the simulations and the experiments with an active knee orthosis.

Since the experimental results in Fig. 5.23 only show that the assistive torques to practice the normal gait motions are adequately generated by the proposed method, the actual effectiveness of the proposed method in the rehabilitation treatment should be verified by clinical tests. Thus, as future work, the proposed gait rehabilitation strategy will be applied to the patients with degenerated nerve systems, and the status of patients will be checked for an extended period of time to observe the improvement. Body weight support systems may be used for better rehabilitation considering the status of patients.
Chapter 6

Concluding Remarks and Open Issues

6.1 Concluding Remarks

This thesis investigated several mechatronic technologies of assistive systems for gait rehabilitation, including (1) estimation and evaluation of the patient’s status (2) monitoring systems, (3) control of assistive systems, and (4) implementation of rehabilitation algorithms.

6.1.1 Estimation and Evaluation of the Patient’s Status

Estimation and evaluation of the patient’s status based on pertinent measurements is the first step toward determining appropriate rehabilitation intervention methods. In Chapter 2, the gait phases were estimated using a hidden Markov model (HMM) based on the ground reaction forces (GRFs) measured by force sensors embedded in shoes, called Smart Shoe. The estimated gait phases were utilized for indicating the patient’s status as well as control of the assistive systems for rehabilitation as discussed in Chapters 4 and 5. In Chapter 3, the GRFs and the center of GRFs (CoGRF) were used as visual feedback information of the monitoring system, and the gait abnormality was calculated based on deviations from the normal GRF levels to evaluate the patient’s status. The patient’s status and the effectiveness of the rehabilitation treatments were evaluated by the GRFs, CoGRF, and gait abnormality, and the clinical test results were included in Chapter 3.

6.1.2 Monitoring Systems for Abnormal Gait Diagnosis and Rehabilitation

Monitoring systems that provided visual feedback information to patients and physical therapists were discussed in Chapter 3. A mobile monitoring system was implemented in a hand-held device equipped with a touch screen and provided the GRFs and CoGRF in real time. The patient could practice a normal gait pattern using visual feedback. The concept of the mobile gait monitoring system was extended to a tele-monitoring system that utilized an inertial measurement unit (IMU) and the Internet. Using the tele-monitoring system, rehabilitation treatments could be achieved anywhere anytime.
6.1.3 Control of Assistive Systems for Rehabilitation

The monitoring systems discussed in Chapter 3 may not be sufficient for seriously impaired patients who need assistive torque for recognizing and practicing normal trajectories. In Chapter 4, robust control algorithms for precise and safe generation of the desired assistive torque were discussed. The developed control algorithms were applied to previously developed assistive systems such as a rotary series elastic actuator (RSEA) and a compact rotary series elastic actuator (cRSEA). Also, the cable tension controller for a cable-driven assistive system which was proposed to separate the actuator from the user’s body, was discussed to compensate for the cable friction and maintain cable tension.

6.1.4 Implementation of Rehabilitation Algorithms

In Chapter 5, the decision-making process for rehabilitation was discussed. If the patient’s muscular functions are permanently damaged, then a power augmentation algorithm is applied based on the estimated joint torque. For estimation of the joint torque, a human body model with seven links and four different ground contact conditions classified by gait phases was used. Lagrangian mechanics were utilized for an analysis of the joint torque. For rehabilitation of the muscular or nervous systems, repetitive practice for normal motion trajectories is required. The assistive system applies the appropriate assistive torque to the patient’s joint if the joint deviates from the desired trajectory, to let the patient recognize and practice a normal trajectory. A potential field around the desired trajectory and an iterative learning algorithm inspired by the repetitive gait motions were proposed for determining the desired assistive torque.

Since the research discussed in this thesis are for patients, the performance of the proposed methods cannot be verified by theory or simulation only. Thus, all of the proposed methods have been verified experimentally, some of them including clinical tests by actual patients.

6.2 Open Issues

A variety of mechatronic technologies of assistive systems for gait rehabilitation have been discussed in this thesis, but there remains much room for future improvements. Remaining open issues include the following.

6.2.1 Sensor Fusion for Estimation of Patient’s Status

As mentioned earlier, accurate measurement and estimation of the patient’s status are considered as the most fundamental requirements in rehabilitation systems. In this thesis, GRFs measured by Smart Shoes were mainly used; however, GRFs may not be sufficient for a detailed analysis of the patient’s status. Additional sensors will allow a more accurate analysis of the patient’s
status. The inertial measurement unit (IMU) for the tele-monitoring system described in Chapter 3 is such an addition. Light, compact, and invasive sensors are required for minimal discomfort to patients. Moreover, intelligent sensor fusion algorithms, i.e., how to integrate sensor signals for more accurate estimation, need to be researched.

6.2.2 Tele-Rehabilitation Systems

The tele-monitoring system was briefly discussed in Chapter 3. As future work, tele-assistive systems with actuating capability will be investigated in addition to a tele-monitoring system. In tele-assistive systems, greater attention should be paid to the unavoidable packet loss and time delay in wireless networks. A control algorithm that guarantees robust stability and performance in spite of packet loss and time delay need to be studied. In addition, a communication program between a patient and a physical therapist needs to be implemented with a user-friendly interface for their easy communication each other.

6.2.3 Improved Design for Assistive Systems

In this thesis, active assistive systems that employ a rotary series elastic mechanism were applied to the experiments. However, the hardware was in research stage, and the actuator modules were applied only to the knee. A compact and light assistive system for lower or upper extremities that takes ergonomics into consideration is an important future research task. Even though this thesis focused on the assistive systems for lower extremities, the proposed technologies such as robust control algorithms can be applied to assistive systems for upper extremities.

6.2.4 Energy Scavenging Assistive Systems

The limit of the mobile energy is the last obstacle for the mobile and long lasting assistive system. Assistive systems which scavenge energy from the human body need to be studied to overcome the mobile energy issues. The resistive forces which are applied in the rehabilitation treatments can be used for the generation of energy. For example, the motor in the assistive system can be changed to a regenerative mode to generate energy during the deceleration period in walking.
Bibliography


