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Design and Control of a Network-based Gait Rehabilitation System: A Cyber-Physical System Approach

by

Wenlong Zhang

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

Doctor of Philosophy

in

Engineering - Mechanical Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Masayoshi Tomizuka, Chair
Professor J. Karl Hedrick
Professor Murat Arcak

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Design and Control of a Network-based Gait Rehabilitation System: A Cyber-Physical System Approach

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Wenlong Zhang
Abstract

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Doctor of Philosophy in Engineering - Mechanical Engineering

University of California, Berkeley

Professor Masayoshi Tomizuka, Chair

Our society is witnessing an unprecedented, enduring, and pervasive aging process. With more and more people requiring walking assistance, the demand for gait physical therapy and rehabilitation has increased rapidly over the years. Current gait rehabilitation therapy relies on physical therapists to make evaluations and provide manual assistance, which is inaccurate and labor intensive. Introducing mechatronic techniques into gait rehabilitation can significantly improve the diagnosis and correction of gait abnormalities. This dissertation proposes a network-based gait rehabilitation system (NGRS) to achieve in-home rehabilitation, with physical therapists monitoring the rehabilitation training progress remotely.

The NGRS includes two main components: a wireless human motion monitoring system for gait analysis and a robotic assistive device controlled wirelessly for active gait correction. The NGRS is clearly a cyber-physical system (CPS) since it involves sensors and actuation devices, communication networks, and computational resources for perception and control. A general design framework is proposed for the design of CPS and the NGRS is developed using this framework as an example. This dissertation is divided into two parts, with the first part handling motion perception and gait analysis, and the second part developing fundamental networked control approaches for the robotic assistive device.

In the first part, design of the wireless human motion monitoring system is illustrated. The system includes a pair of wireless smart shoes embedded with barometric sensors for gait phase detection, and several wireless joint angle sensors for joint kinematic analysis. User interfaces are developed on both a laptop and an iPad to demonstrate processed sensory data as real-time visual feedback. It is shown that the sensory data make it more convenient and accurate to distinguish pathological gait from normal gait. Clinical effectiveness of visual feedback is verified with 24 stroke and Parkinson’s disease patients.

In the second part, networked control systems (NCSs) are designed to achieve wireless motion control of the robotic assistive device. In this part, emphasis is given to the compensation of time delay and packet loss during wireless communication. For time delay compensation, two different approaches are presented. The first approach utilizes the de-
lay measurement to build an equivalent system model, and an optimal preview controller is designed to utilize future reference signals for additional feedforward control. A double disturbance observer (DDOB) is developed to adaptively compensate for the time delay without any delay models or measurements. For packet loss compensation, two approaches are developed as well based on the Bernoulli packet loss model. The first technique is an extension of the modified LQG (MLQG) controller by adding a disturbance observer (DOB) for robustness enhancement. The preview control is also employed for packet loss compensation as the second approach. All techniques proposed in this part are validated by simulation and experimental results.
To my family
Contents

List of Figures v
List of Tables viii

1 Introduction 1
  1.1 Assistive Systems for Gait Rehabilitation: Necessary but not Sufficient . . . 1
  1.1.1 Challenges and Motivation ........................................ 1
  1.1.2 State of the Art ..................................................... 3
  1.2 Network-based Gait Rehabilitation System for In-home Rehabilitation . . . 7
  1.3 System Design as a Cyber-Physical System .......................... 9
  1.4 Thesis Overview ..................................................... 12

2 A Wireless Human Motion Monitoring System for Gait Analysis 14
  2.1 Introduction .......................................................... 14
  2.2 System Overview ..................................................... 16
    2.2.1 Rehabilitation Training with Visual Feedback .......................... 16
    2.2.2 System Structure ................................................... 17
  2.3 Wireless Joint Angle Sensors ....................................... 18
    2.3.1 Hardware Design .................................................. 18
    2.3.2 Filtering Algorithm and Joint Rotation Calculation ................. 19
    2.3.3 Performance Evaluation of the IMU Sensors ........................ 21
  2.4 Wireless Smart Shoes ............................................... 21
  2.5 Calculation of Gait Phases and Kinematic Information ............... 22
    2.5.1 Gait Phases ....................................................... 22
    2.5.2 Center of Pressure ................................................. 24
    2.5.3 Stride Length and Step Length .................................. 24
    2.5.4 Toe-out Angle ..................................................... 26
    2.5.5 Stride Width ..................................................... 26
  2.6 Design of User Interfaces .......................................... 26
    2.6.1 Visual Feedback on a Laptop .................................... 26
2.6.2 Visual Feedback on an iPad ................................................. 27
2.7 Experimental Results ......................................................... 27
  2.7.1 Experimental Results of A Healthy Subject ......................... 28
  2.7.2 Experimental Results of A Stroke Patient .......................... 31
2.8 Chapter Summary ............................................................. 32

3 Clinical Study on the Effect of Visual Feedback in Gait Rehabilitation 34
  3.1 Introduction ............................................................... 34
  3.2 Procedures of the Clinical Study ....................................... 35
    3.2.1 Selection of Human Subjects ...................................... 35
    3.2.2 Gait Training ...................................................... 35
    3.2.3 Baseline and Post-training Evaluations .......................... 36
    3.2.4 Statistical Data Analysis ....................................... 39
  3.3 Experimental Results .................................................... 40
    3.3.1 Baseline Evaluations ............................................. 40
    3.3.2 Results across All Subjects .................................... 40
    3.3.3 Results by Diagnostic Groups .................................. 41
    3.3.4 Results across the Control and Experimental Groups ............ 43
    3.3.5 Discussion of Clinical Evaluation Results ...................... 45
  3.4 Statistical Analysis of Training Performance Based on Sensory Data .. 48
    3.4.1 Proposal of Gait Parameters .................................... 48
    3.4.2 Training Progress Evaluation of a Stroke Patient ............... 49
  3.5 Chapter Summary .......................................................... 50

4 Networked Control of an Assistive Robot: Time Delay Compensation 52
  4.1 Introduction ............................................................. 52
  4.2 Design of the RT-WiFi Wireless Protocol ............................. 54
    4.2.1 RT-WiFi: Real-time Wireless Protocol for High-speed Networked Control Systems ................................................. 55
    4.2.2 Network Performance .............................................. 56
  4.3 Time Delay Compensation with Optimal Preview Control .............. 58
    4.3.1 System Model with Time Delay .................................. 58
    4.3.2 Preview Controller Design ...................................... 59
    4.3.3 Simulation Study and Discussions ................................ 65
  4.4 Time Delay Compensation Based on Double Disturbance Observers .... 69
    4.4.1 System Modeling with Time Delay as Network Disturbance ....... 70
    4.4.2 A Double Disturbance Observer Design for Time Delay Compensation ......................................................... 71
    4.4.3 Performance Analysis and Simulation Results ................... 75
    4.4.4 Experimental Study .............................................. 78
  4.5 Chapter Summary .......................................................... 80

5 Networked Control of an Assistive Robot: Packet Loss Compensation 81
5.1 Introduction .......................................................... 81
5.2 A Compact Rotary Series Elastic Actuator ....................... 82
5.3 Packet Loss Modeling ................................................. 83
5.4 Data Transfer via the Internet ....................................... 84
5.5 Modified LQG Control for Packet Loss Compensation ........ 86
  5.5.1 Controller Design ............................................... 86
  5.5.2 Simulation Study .............................................. 90
  5.5.3 Performance Verification by Experiments ................... 92
5.6 Packet Loss Compensation: A Modified Preview Control Approach ........ 94
  5.6.1 Modified Preview Controller Design ......................... 94
  5.6.2 Simulation Study .............................................. 98
  5.6.3 Experimental Study ........................................... 106
5.7 Chapter Summary .................................................. 108

6 Conclusions and Open Problems ........................................ 109
  6.1 Concluding Remarks ............................................. 109
  6.2 Open Problems ................................................. 111

Bibliography ................................................................... 113
List of Figures

1.1 Changes in demographic structures of the world [1] .......................... 1
1.2 Changes in demographic structures in major countries [1] .......................... 2
1.3 Traditional rehabilitation .......................... 3
1.4 Problems of the current rehabilitation training .......................... 4
1.5 Sensors for walking pattern analysis and health monitoring .......................... 5
1.6 Power augmentation systems and their applications to gait rehabilitation .......................... 6
1.7 Examples of gait rehabilitation systems .......................... 6
1.8 Structure of the networked gait rehabilitation system .......................... 7
1.9 Comparisons of traditional rehabilitation and proposed rehabilitation frameworks .......................... 8
1.10 Examples of cyber-physical systems .......................... 10
1.11 Multi-layer framework for design of a cyber-physical system .......................... 11

2.1 A block diagram of the rehabilitation training with visual feedback .......................... 16
2.2 Structure of the wireless human motion monitoring system .......................... 17
2.3 Wireless joint angle sensor: first generation .......................... 18
2.4 Wireless joint angle sensor: second generation .......................... 19
2.5 Setup of the markers and IMU sensors .......................... 20
2.6 Joint angles of squat in the sagittal plane from cameras and IMU sensors .......................... 21
2.7 Wireless smart shoes for gait detection .......................... 22
2.8 Gait phases [56] and corresponding GCF patterns [8] .......................... 23
2.9 Foot placement on the ground and corresponding joint rotation .......................... 25
2.10 Geometry for step length calculation .......................... 25
2.11 Visual feedback on a laptop .......................... 27
2.12 User interface of the iPad application for visual feedback .......................... 28
2.13 An iPad holder .......................... 28
2.14 Experiment of the wireless human motion monitoring system with a healthy subject .......................... 29
2.15 Comparisons of gait phase detection algorithms .......................... 29
2.16 caption .......................... 30
2.17 Joint angle statistics (left: healthy subject, right: stroke patient) .......................... 31
2.18 Center of pressure from two subjects during walking .......................... 32

3.1 Design of the clinical study .......................... 36
3.2 Gait parameters before and after rehabilitation training for a stroke patient ........ 50
4.1 Block diagram and challenges of a networked control system (NCS) .......... 53
4.2 Performance of the current wireless protocols and RT-WiFi .................. 54
4.3 Time delay measurement in the Ethernet link ................................. 55
4.4 Time delay measurement in the RT-WiFi network ............................. 56
4.5 Configuration of testbed ..................................................... 57
4.6 Signal transmission in a NCS with a maximum round-trip delay of $n_0$ steps .. 60
4.7 Representation of the preview control problem ............................ 61
4.8 Block diagram of the proposed preview controller ................................ 65
4.9 Reference trajectory from reference generator .................................. 66
4.10 Performance of the Kalman filter with time-varying delay .................. 67
4.11 Simulation results with $N_p = 50$ ........................................ 68
4.12 Conceptual block diagram of time delay compensation with a CDDB ........ 71
4.13 Block diagram of a networked motion control system with a CDDB ........ 72
4.14 Robust controller design in a networked motion control system with DDDBs .. 74
4.15 Reformulation of the DDDB block diagram ................................... 75
4.16 Bode plot of closed-loop transfer functions with different baseline controllers (dotted line: $K_p = 0.4, K_d = 0$; solid line: $K_p = 0.6, K_d = 0.01$; dot dashed line: $K_p = 0.8, K_d = 0.01$; dashed line: $K_p = 0.8, K_d = 0.02$) ................. 76
4.17 Magnitude of $K_2$, $W_m^{-1}$, and modeling uncertainties ..................... 77
4.18 Simulation results with different control structures ........................... 78
4.19 Experimental results with different control structures and baseline controllers .. 79
5.1 Compact rotary series elastic actuator (cRSEA) and the mechanism [140] ....... 83
5.2 Transmission of desired assistive torques in TCP with or without a packet buffer 85
5.3 A basic block diagram of disturbance observer (DOB) ($y_d$: reference, $y$: output, $u$: control input from controller $C$, $u_d$: control input to cancel disturbance $d$, $\hat{d}$: estimated disturbance, $P_n$: nominal model of plant $P$, $Q$: $Q$ filter) ......... 88
5.4 Overall structure of the proposed controller for a network-based rehabilitation system ($P$: actuator in the rehabilitation system, $P_n$: nominal model of $P$, $Q$: $Q$ filter in the DOB) ......................................................... 88
5.5 Desired motor trajectory for the simulation study .................................. 90
5.6 Simulation results of different packet loss compensation algorithms .......... 91
5.7 Experimental results: no knee motion, 10% packet loss rate .................. 93
5.8 Experimental results: arbitrary knee motion, 10% packet loss rate .......... 93
5.9 Torque error: arbitrary knee motion, 30% packet loss rate .................... 94
5.10 Block diagram of the modified preview control system ....................... 97
5.11 Reference signals from reference generator .................................. 98
5.12 Performance of the Kalman filter with 20% packet loss ........................ 99
5.13 Simulation results of modified preview controllers with an open-loop stable plant 100
5.14 Simulation results with different preview horizons and an open-loop stable plant 102
5.15 Simulation results of modified preview controllers with an open-loop unstable plant

5.16 Simulation results with different preview horizons and an open-loop stable plant

5.17 Configuration of experimental setup

5.18 Experimental results of modified preview controllers

6.1 Layered design of the networked rehabilitation system using a cyber-physical system approach
List of Tables

3.1 Types of task specific activities integrated into gait training - part I .......................... 37
3.2 Types of task specific activities integrated into gait training - part II .......................... 38
3.3 Types of task specific activities integrated into gait training - part III .......................... 39
3.4 Baseline differences following random assignment to control and experimental groups: stroke patients .......................................................... 40
3.5 Baseline differences following random assignment to control and experimental groups: Parkinson's disease patients ........................................ 41
3.6 Pre, post and post-pre mean change scores on all dependent variables across all subjects .......................................................... 42
3.7 Descriptive changes in signs and symptoms across all subjects .................................. 42
3.8 Pre, post and post-pre test gain scores within the group of stroke patients .................. 43
3.9 Pre, post and post-pre test gain scores within the group of PD patients ....................... 44
3.10 Pre, post and post-pre test gain scores between diagnostic groups ............................ 44
3.11 Post and pre test difference scores: control and experimental groups ...................... 46
3.12 Post-pre test gain scores within diagnostic groups: experimental and control groups 47
3.13 Change of gait parameters based on sensor measurements (SS: smart shoes; JAS: joint angle sensors) .......................................................... 48

4.1 Comparison of the two feedforward delay estimation methods ........................................ 66
4.2 RMS tracking errors under different preview horizons and delay estimation methods (deg) .......................................................... 68
4.3 Values of cost function under different preview horizons and delay estimation methods .......................................................... 69
4.4 Closed-loop transfer functions for controllers with CDOB only .................................... 73
4.5 Closed-loop transfer functions for controllers with DDOBss ........................................ 74
4.6 Comparison of RMS tracking errors with different controllers in simulations (deg) ........ 77
4.7 Comparison of RMS tracking errors with different controllers in experiments (deg) ....... 79

5.1 RMS of tracking errors (deg) ....................................................................................... 91
5.2 RMS tracking errors in simulations with an open-loop stable plant (deg) ...................... 101
5.3 Values of cost function in simulations with an open-loop stable plant .......................... 101
5.4 RMS tracking errors in simulations with an open-loop unstable plant (deg) ................ 104
5.5 Values of cost function in simulations with an open-loop unstable plant . . . . . 104
5.6 RMS tracking errors in experiments (deg) . . . . . . . . . . . . . . . . . . . . . . . . . . 107
5.7 Values of cost function in experiments . . . . . . . . . . . . . . . . . . . . . . . . . . . . 108
Nomenclature

3D three dimensional
AP access point
CDOB communication disturbance observer
CoP center of pressure
CPS cyber-physical system
cRSEA compact rotary series elastic actuator
DDOB double disturbance observer
DOB disturbance observer
EMG electromyogram
FMV fuzzy membership value
FSR force-sensitive resistor
GCF ground contact force
GMC Gaussian mixture classifier
GMM Gaussian mixture model
HMM hidden Markov model
IMU inertial measurement unit
LMI linear matrix inequality
LQG linear quadratic Gaussian
MLQG modified linear quadratic Gaussian
NCS networked control system
NGRS  networked gait rehabilitation system
PD    Parkinson’s disease
RMS   root mean square
RoM   range of motion
TCP   transmission control protocol
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Chapter 1

Introduction

1.1 Assistive Systems for Gait Rehabilitation: Necessary but not Sufficient

1.1.1 Challenges and Motivation

The world is experiencing an unprecedented, enduring, and pervasive aging process [1]. Figure 1.1 shows the demographic structure of world population in 1950, 2000, and 2050 (projected). It can be clearly observed that the proportion of elderly people has increased and the aging process will probably continue. This trend is also observed in major countries such as United States (shown in Fig. 1.2a) and China (shown in Fig. 1.2b). Aging not only contributes to integrative challenges to memory, balance, and mobility for healthy subjects, but also leads to degenerative conditions of the musculoskeletal system (such as osteoporosis and arthritis), the cardiovascular system (such as heart failure and arrhythmia), and internal organs (such as diabetes).

Another major consequence of aging is neurological impairments (such as Alzheimer’s disease [2], stroke [3], and Parkinson’s disease [4]). According to [3], nearly three quarters of all strokes occur in people over the age of 65. The risk of having a stroke more than

Figure 1.1: Changes in demographic structures of the world [1]
doubles each decade after the age of 55. Stroke is the leading cause of serious, long-term disability in the United States. Each year, approximately 795,000 people suffer a stroke, which means there is on average one stroke attack every 40 seconds in the United States [3]. Approximately 60,000 Americans are diagnosed with Parkinson’s disease each year [4]. Major sequelae of stroke and Parkinson’s disease include various gait abnormalities, such as foot dragging, weak heel and toe support, asymmetric step length, and so on.

Besides aging, we are facing a fast increase of sports injuries. According to the U.S. Consumer Product Safety Commission’s National Electronic Injury Surveillance System (NEISS), more than 1.9 million individuals had a sports-related injury that was treated in emergency departments in 2012 [5]. In summary, aging, neurological diseases, and sports injuries all lead to gait training. With more people who need walking assistance, the challenge is to help individuals maintain independence at home and participate in the society. As a consequence, the demand for gait physical therapy and rehabilitation has increased rapidly over the years.

Current gait rehabilitative therapy is provided by physical therapists who stimulate patients’ reflexes as well as use manual techniques to facilitate their walking, as is shown in Fig. 1.3. Even with body un-weighting, therapists often need to help patients step with the affected limb. This is not only physically demanding for both patients and therapists, but also expensive and time-consuming. Moreover, current assessment of gait impairments is based on the visual observation of therapists, video analysis, physical tests (strength, range

Figure 1.2: Changes in demographic structures in major countries [1]
of motion, balance, gait speed, and endurance), as well as self-reports from patients (confidence, resilience, fatigue, and falls). Therapists usually do not have access to real-time measurement of ground contact forces (GCFs), timing sequence of gait cycles, or accurate information of step length and velocity of patients. Therefore, current gait evaluation is quite subjective and it puts really strict requirements on physical therapists.

Since a physical therapist needs to work very closely with the patient, usually one physical therapist can work with only one patient at a time. This type of one-to-one physical therapy makes the physical therapists in short supply and it greatly limits the number of patients who can receive the appropriate gait training and. It also makes the gait rehabilitation therapy more and more expensive. Moreover, due to the nature of the current physical therapy, patients need to visit a rehabilitation clinic to receive the treatment, which is very inconvenient due to their walking difficulties. Figure 1.4 summarizes the challenges of the current rehabilitation training.

1.1.2 State of the Art

Motivated by the aforementioned challenges, researchers have developed various kinds of sensing and actuation devices to improve the performance of gait rehabilitation training. This subsection provides a summary of the gait monitoring devices and assistive robots.

As the first step of providing walking assistance, different types of human motion monitoring systems have been developed for gait perception. To name a few, electromyogram (EMG) sensors were used to analyze the electrical activity of the contracting muscles [6, 7]. Pressure sensors and force plates were adopted to measure the GCFs for analysis of walking patterns [8, 9]. As a commercialized product, XSens developed the ForceShoe to acquire
three-dimensional (3D) measurement of forces, torques and kinematic information of the foot for gait analysis [10]. Tekscan introduced \textit{F-scan} in-shoe analysis system to wirelessly measure the pressure on feet during walking [11].

For human motion tracking, camera-based sensors were also employed for reconstruction of human motion [12, 13], and some commercialized products include Vicon [14] and PhaseSpace [15] motion capture systems. Inertial sensors were widely used to estimate the joint rotations of lower extremity during walking [16, 17]. Both inertial sensors and vision sensors can measure joint rotations, and the latter may provide more accurate results. However, vision sensors are expensive and signal processing algorithms are complicated. Moreover, they need to be fixed in an indoor environment and users can only walk in a limited clear space. On the contrary, inertial sensors are less expensive and more mobile. Xsens developed \textit{MTw} to achieve 3D kinematic measurement for walking pattern recognition. The \textit{MTw} utilizes inertial sensors to get raw data and a wireless module to transmit the sensing signals over a wireless network [18, 19, 20]. Another wireless sensor platform for walking pattern analysis is \textit{Shimmer} [21], whose attractive characteristics include high-speed microcontroller, flexible sensor configuration, and large data storage. See Fig. 1.5 for some examples of the commercialized health monitoring systems. For a comprehensive review of the research progress of human motion monitoring system, see [22].

In addition to the rapid development of passive health monitoring system, active rehabilitation robots are desirable to provide assistive torque to patients. In this case, a physical therapist does not need to move patients’ joints manually and they can focus on making decisions of rehabilitation strategy. Therefore, rehabilitation robots have received considerable investigation and many researchers have put forward their own designs.

Power augmentation systems are one type of robots which can provide assistive torque
to soldiers or emergency personnel to carry heavy loads. The Hybrid Assistive Limb (HAL) shown in Fig. 1.6a is designed by Sankai at University of Tsukuba. It is a cyborg-type robot that can expand and improve physical capability. The HAL catches the nerve signals through several EMG sensors attached on the skin of the wearer, and the power unit is then controlled to move the joint unitedly with the wearer’s muscle movement. Its height is about 1600 mm and weight is approximately 23 kg. A chargeable battery is used as a power supply and it can work up to 160 minutes [23, 24]. The HAL was also used to assist patients with weakened muscles, see Fig. 1.6b. The Berkeley Lower Extremity Exoskeleton (BLEEX) designed by Kazerooni at UC Berkeley is a self-powered exoskeleton for strength and endurance enhancement of humans, see Fig. 1.6c. It enables its users to carry heavy loads with minimal effort. The BLEEX utilizes sensors in the shoes to detect gait information and use positive feedback control of a hydraulic actuator to increase the sensitivity of the closed system to the torque and force, i.e., the user can perform the same task with less muscular power [25, 26]. The same team also developed a new commercialized product called eLEGS for gait rehabilitation [27], see Fig. 1.6d.

The HAL and eLEGS are converted from power augmentation devices for gait rehabilitation. There are also some commercialized products that are originally designed for gait rehabilitation. Lokomat system shown in Fig. 1.7a is a gait orthosis for robotic treadmill training of neurological disease patients with movement disorders [28, 29]. The patients’ legs are guided on the treadmill according to a pre-programmed physiological gait pattern. Motors are appropriately controlled to provide assistive torque to move the patients’ legs. It provides body weight support and visual feedback to the patients during rehabilitation training. Several clinical tests were conducted to verify the performance of Lokomat system during rehabilitation sessions [30, 31]. The Tibion Bionic Leg shown in Fig. 1.7b is a wearable robotic device on lower extremity. It employs plantar pressure sensors to detect gait phase. During the stance phase, stair ascent or sit-to-stand movements, the knee actuator actively assists concentric extension. At toe-off, during the swing phase or in non-weight bearing, the actuator decouples to allow free knee swing. At heel strike, stair descent or
stand-to-sit, the knee actuator resists knee flexion by providing an eccentric knee extension torque [32, 33]. The result of the clinical test showed its effectiveness for stroke patients [34].

Besides commercialized products, many research projects on gait rehabilitation robots are ongoing to better serve elderly people and patients with neurological impairments. Hogan at MIT designed rehabilitation device for different human joints including wrist and ankle [37, 38]. Scholz at University of Delaware developed active leg exoskeleton (ALEX) which has multiple degrees of freedom that allow a more natural walking ability of the user [35], see Fig. 1.7c. Herr at MIT developed an active ankle-foot orthoses (AAFO) for drop foot gait rehabilitation [39]. Mavroidis at Northeastern University developed active knee rehabilitation orthotic device (AKROD) using nonlinear adaptive control [36], see Fig. 1.7d. For a complete review of designing and controlling rehabilitation robots, see [40, 41].
1.2 Network-based Gait Rehabilitation System for In-home Rehabilitation

The plan of gait rehabilitation training should integrate objective findings into a goal-oriented, task-specific, repetitive, and progressive learning-based retraining program. This type of program can require multiple visits to the rehabilitation clinics, which could be inconvenient and expensive to patients. The outcomes of the intervention should be associated with objective improvement in impairments as well as measurable improvement in functional independence and community participation.

Motivated by the aforementioned challenges, a network-based gait rehabilitation system (NGRS) is proposed in this dissertation to achieve in-home rehabilitation. The structure of the proposed system is shown in Fig. 1.8. The system includes two parts, one located at the patient side and the other located at the therapist side. At the patient side, a patient conducts gait exercises with several wearable sensors, and sensing information is wirelessly transmitted to a local computer. The sensing information is then processed and gait analysis results will be shown via a user interface to provide visual feedback. A wearable robotic device is also developed to provide active assistance to the patient’s knee joint. The assistive device is controlled over the real-time and high-speed wireless network to achieve improved mobility.
and reduced weight. All sensing and control signals are stored in the local computer, which is connected to the therapist side. In summary, the local computer has the following four main functions:

- Data processing: It is used to receive raw sensing data and perform basic data processing. For example, sensor noise can be filtered, gait information can be extracted from the sensing data, and sensor fusion can be performed to get more comprehensive knowledge of the patients’ walking dynamics.

- Data transmission: Once the data processing is completed, the local computer encapsulates the processed data into a packet, and sends it to the host computer through Internet. At the same time, it receives command signals from the host computer and physical therapist side via Internet. The command signals include reference signals for the motion control system and comments from the physical therapists to the patients.

- Low-level control: It can calculate control signals based on the embedded control algorithms, sensing information, and reference signals from the physical therapist side. Then the control signals are sent to the actuator over the wireless network.

- User interface: It acts as a user interface for the patient to receive visual feedback, observe the progress of rehabilitation treatment, and send their comments to the physical therapist.

In the remote side, high-level decision making algorithms, which conduct disease diagnosis and trajectory planning of the assistive robot, are implemented in the high-level controller. The high-level controller can be on a single high-performance host computer or a cloud-computing platform depending on the amount of service it needs to provide. Each local
computer is connected to the high-level controller through Internet and information from the local side can be shared with the physical therapist side. A physical therapist can connect to the high-level controller to access the measurement in real-time and provide feedback to the patient or change the plan of gait exercise. All data can be securely stored in the database for further pathological studies.

Figure 1.9 shows the comparison between the traditional rehabilitation framework and the proposed networked rehabilitation. The lower part shows the block diagram of traditional rehabilitation strategy and the upper one represents the proposed approach. It can be verified that each element of the proposed NGRS realizes part of the therapist’s functions. For example, the computer in the system is analogous to the therapist’s brain to process the measurement data and perform robot trajectory planning, and the active assistive device is similar to the therapist’s muscles to provide active assistance for gait corrections. This system changes the traditional manual rehabilitation treatment to smart rehabilitation by introducing the sensing and actuation devices. It is expected that by moving gait rehabilitation training to patients’ homes, patients do not need to visit the rehabilitation clinics. Moreover, since most of the work can be conducted by the system automatically, one therapist can work with multiple patients simultaneously, which helps solve the lack of physical therapists. Checking Fig. 1.4 indicates that the proposed system fundamentally solves the problems of the current rehabilitation treatment and makes it more efficient and user-friendly.

1.3 System Design as a Cyber-Physical System

In this dissertation, design of the NGRS is viewed as a cyber-physical system (CPS) and some broad challenges are addressed. The term “cyber-physical system” was first proposed by Dr. Helen Gill at the National Science Foundation around 2006, and it refers to the next generation of engineered systems that require tight integration of computing, communication, and control technologies to achieve stability, performance, reliability, robustness, and efficiency in dealing with physical systems of many application domains [42]. Some examples of CPSs can be found in Fig. 1.10. The CPS has attracted a lot of attention recently, especially in the fields of control and communication. The importance of the CPS has been clearly recognized in the 2007 report of the USA President’s Council of Advisors on Science and Technology (PCAST) and National Science Foundation has identified the CPS as one of the key areas of research [43]. Given its great impact on the design of next-generation engineering systems, IEEE Transactions on Automatic Control has published a special issue focusing on the control system design of CPSs [43].

In order to systematically design a CPS, there are several challenges that the designers need to handle carefully [44]. The first one is the communication protocol design. In order to support accurate perception of each agent’s behavior, the communication protocol needs to have enough bandwidth to support high-speed and real-time data transmission [45]. The second one is the hybrid control of the physical plant, and this comes from the fact that a
CPS usually needs to switch between different operating modes to adapt to the changing environment [46, 47, 48]. The third problem is the networked control and coordination. Since there are many agents in a CPS and they are connected through communication networks, it is very important to achieve both high-level behavior coordination [49, 50] and low-level motion control [51, 52] over the communication networks. The main challenges brought by the communication network is the imperfect transmission of data packets, such as time delay and packet loss. There are several other challenges that require the co-design between the communication and control engineers, such as security [53, 54] and power consumption [55].

It is clear that the proposed NGRS features a tight integration of its physical plants, computational resources, communication, and control systems. Therefore, it is a clearly a CPS and this dissertation will go beyond the design of a specific CPS and answer some of the fundamental problems in a CPS. This allows us to bring our design philosophy into other CPSs, such as human-robot interactions, autonomous vehicles, energy systems, and so on. The following three fundamental problems are addressed:

- What is the general framework for the design of a CPS?
• How to achieve accurate perception of agents in a CPS and provide user-friendly feedback?

• How to guarantee stability and performance during networked control and coordination in a CPS?

For the first question, Fig. 1.11 shows our proposed multi-layer design framework of a CPS. In the hardware layer, the basic elements (sensors, controllers, and actuators) need to be developed to lay out the foundation of system functionalities. The communication level requires the design of communication protocols to support data exchanges between agents in the system. Once basic hardware and communication are set up, measurement and control data start to be generated and they need to be well managed so as to achieve secure data storage and efficient indexing. This is especially important if the system scale goes large. The perception level requires algorithms to understand each agent’s behavior as well as the interactions between agents. Once the whole system dynamics is identified, control algorithms can be then designed to coordinate each agent’s behavior and achieve desired system functionalities. At the top level, the prototype system needs to be put into the real application environment to examine its performance before batch production. The second problem of sensing and perception will be investigated in Chapters 2 and 3, and the third problem of networked control will be studied in Chapters 4 and 5.
CHAPTER 1. INTRODUCTION

1.4 Thesis Overview

In order to handle the challenges mentioned above, this dissertation aims at solving both fundamental and practical problems in the design of the NGRS using a CPS approach. Using the general design structure given in the last subsection, Chapters 2 and 3 will discuss the human motion perception and solve second fundamental problem regarding sensing and perception. Chapters 4 and 5 will address the third fundamental problem of networked control and coordination, using the design of networked motion control system with time delay and packet loss. The dissertation is organized as follows:

Chapter 2: A Wireless Human Motion Monitoring System for Gait Analysis

This chapter introduces the design of a wireless human motion monitoring system for gait analysis, and this chapter sets the foundation for human motion perception and biofeedback. Two types of wireless sensory devices, smart shoes and joint angle sensors, are introduced to measure the GCFs and joint kinematics of lower extremity respectively. User interfaces are developed to deliver visual feedback to patients and therapists during rehabilitation training. The system is applied to both healthy subjects and patients, and experimental results clearly show the different gait characteristics.

Chapter 3: Clinical Study on the Effect of Visual Feedback in Gait Rehabilitation

In order to verify that the real-time visual feedback from the human motion monitoring system can help patients during rehabilitation training, the system is applied in a clinical study with 24 stroke and Parkinson’s disease (PD) patients. Those patients are randomly assigned to a control or experimental group, where patients in the former one receive traditional treatment guided by therapists and patients in the latter one utilize visual feedback to guide their gait training. The improvement of gait is characterized using both standardized clinical tests and sensory data. It is shown that patients in both groups achieve similar improvement in gait, which suggests the good performance of rehabilitation guided by the visual feedback from sensory data.

Chapter 4: Networked Control of an Assistive Robot: Time Delay Compensation

Once the trajectory planning of the assistive robot is completed, the next step is to make the actuator track the desired trajectory. In order to achieve improved mobility, the assistive robot is controlled over the wireless network and there are many technical challenges associated with this approach. In this chapter, the negative effect of time delay is discussed and two approaches are proposed to compensate for time delay. The first approach is based on the preview control, where a delay measurement is used to build the equivalent system model and future reference signals are applied to design the feedforward controller. As the
second approach, a double disturbance observer (DDOB) approach is proposed to cancel the negative effect of the time delay without any delay measurement or model. Simulation and experimental results are shown to validate the performance of the proposed algorithms.

Chapter 5: Networked Control of an Assistive Robot: Packet Loss Compensation

This chapter handles packet loss in a networked control system (NCS). The packet loss modeling is first discussed and two approaches are proposed to control the assistive device with random packet loss. The first approach is based on the modified linear quadratic Gaussian (LQG) control, and a disturbance observer (DOB) is employed as the internal loop compensator to improve the robustness of the system. The second approach is based on the preview control, and future reference signals are used to improve the system response via additional feedforward control. Simulation and experimental results are presented to verify the controller design.

Chapter 6: Conclusions

Concluding remarks of this dissertation are drawn and some open issues are discussed as future work.
Chapter 2

A Wireless Human Motion Monitoring System for Gait Analysis

2.1 Introduction

Gait analysis is the first step for providing walking assistance. Currently gait analysis is provided by physical therapists who make decisions based on visual observations and physical tests, which is time-consuming and inaccurate. This motivates researchers to introduce sensory devices to analyze walking patterns and improve the gait evaluations.

Gait phases have been widely accepted as a powerful tool of studying human gait [56, 57], and they can be extracted from the GCF measurement. Researchers have developed different devices to measure GCFs and detect gait phases. Four force-sensitive resistors (FSRs) and two polyvinylidene fluoride (PVDF) strips were embedded in the shoe pad to measure the force and pressure for gait analysis [58]. An insole with 12 FSRs was designed to embed into a shoe to achieve more comprehensive gait analysis based on detailed force measurement [59]. Fabric pressure sensing array was employed to measure plantar pressure during walking for gait analysis [60]. GCF measurement was displayed on a smart phone to make patients better understand their walking abnormalities [61].

In our previous work, a measurement device called smart shoes was developed by Kong and Tomizuka to measure the GCFs and gait phases were then extracted by fuzzy logic [8]. Bae et al. proposed to use hidden Markov models (HMMs) to detect gait phases and evaluate the gait abnormalities based on GCF measurement [62]. Mobile display was designed to provide visual feedback on the difference between measured GCFs and normal GCFs. Clinical studies were conducted with seven patients to preliminarily verify the effectiveness of the gait training with visual feedback.

Besides smart shoes, inertial measurement unit (IMU) sensors have also been frequently employed to measure joint kinematics of lower extremity. An IMU sensor usually includes an accelerometer, gyroscope, and magnetometer. The IMU sensor was often combined with in-shoe pressure sensors to achieve more comprehensive gait evaluation [58, 63, 9]. Besides gait
analysis, IMU sensors were also widely used for fall detection \cite{64,65} and localization \cite{66,67}. The main challenge of applying IMU sensors lies in the signal processing because of the noisy acceleration, drifted rate, and distorted magnetic field measurements. Different filtering algorithms, including Kalman filters \cite{68}, extended Kalman filters \cite{69}, and complementary filters \cite{70}, were developed to achieve accurate orientation estimation.

Despite all the human motion monitoring systems mentioned above, there are still some problems that need to be solved before those systems can be used in clinical rehabilitation, which include

- **Introduction of biofeedback:** although quite a few sensors can measure the information about users’ walking dynamics, many of them are just used to record the data instead of providing useful feedback to the users, which is necessary in order to perform active intervention to the patients.

- **Visual feedback design:** it is clearly not a good idea to display all measurement data to patients as they may not be able to understand and digest the overwhelming messages. Moreover, too much visual feedback will distract patients’ attention and make it difficult for them to focus on correcting their gait patterns. As a result, only selected useful feedback should be displayed to patients.

- **Overall mobility:** despite wireless technology being widely used in human motion capture systems, the receiver of the sensor signals is usually a laptop or desktop computer, not patients. Even with display on a laptop, the patient cannot look at the computer screen when they perform selected rehabilitation exercise. Therefore, a wireless mobile display needs to be developed for the patients.

- **Usability:** patients will easily get bored if they conduct the rehabilitation training for a long period, so it is important to make the training process engaging and informative so that they can be motivated to continue the rehabilitation training.

In this chapter, a wireless human motion monitoring system is designed, including both wireless smart shoes and joint angle sensors. Visual feedback is developed based on both laptops and mobile devices such as an iPad, which makes it possible for patients to receive real-time and intuitive feedback to help them better understand their gait abnormalities. Design of sensory devices and visual feedback will be illustrated, and experimental results will be demonstrated from both healthy subjects and stroke patients to verify the performance of the sensors. The hardware development in this chapter lays foundation for comprehensive gait analysis and clinical studies with visual feedback.
2.2 System Overview

2.2.1 Rehabilitation Training with Visual Feedback

A block diagram of the rehabilitation with visual feedback is shown in Fig. 2.1. In the traditional rehabilitation training, a physical therapist observes the patient’s walking and provides auditory feedback to the patient. The patient then hears the therapist’s command signals and tries to correct his or her gait pattern. In many cases, the physical therapist also provides physical assistance if he or she thinks the patient cannot follow the command signals. It is clear that feedback to the patients is heavily based on the therapists’ knowledge and experience. However, patients’ abnormal walking may not be very obvious for the therapists to observe. Moreover, it is difficult to provide intuitive feedback and evaluate the progress of rehabilitation based on observation only.

To improve the performance and efficiency of the rehabilitation training, new feedback is introduced to patients by utilizing some wireless motion sensors. Selected measurement data from the sensors are shown on a mobile display so that patients can get the visual feedback regarding their gait. The visual feedback, together with the command signals and physical assistance from therapists, helps the patients stimulate their brain for gait correction. The main advantages of the proposed framework include:

- Adding new sensors into the system could provide additional information both qualitatively and quantitatively on gait phase, step length, joint rotation, and timing of gait cycles. This additional information will help patients and physical therapists better understand the walking abnormalities and try to make corrections.

- The mobile feedback makes it easy for patients to observe their walking behaviors in real-time when they are doing the rehabilitation training. Moreover, it is easier for
2.2.2 System Structure

Structure of the proposed system is shown in Fig. 2.2 [71]. In the system, a user walks with a pair of smart shoes and several joint angle sensors. The smart shoes and joint angle sensors send measurement data to a laptop (local computer) wirelessly. A program is developed in a laptop to read the sensor signals through serial ports. The program then processes the raw data from the sensors and sends selected data to an iPad for visual feedback. Bluetooth Low Energy (Bluetooth v4.0) protocol is employed for communication between the laptop and iPad. Alternatively, the user can also choose to open an application program in this laptop to receive the visual feedback. All the raw and processed data are stored in the laptop for further study. In the following sections, components of the wireless human motion monitoring system will be introduced in more details.

Figure 2.2: Structure of the wireless human motion monitoring system
2.3 Wireless Joint Angle Sensors

2.3.1 Hardware Design

There are two generations of wireless joint angle sensors developed to measure the human joint angles in three dimensions. Both generations employ an IMU sensor node to take raw measurements from the onboard accelerometer, magnetometer, and gyroscope, each with three degrees of freedom.

The first generation is a custom design, as is shown in Fig. 2.3a. An Arduino Pro Mini 328 microcontroller [72] is employed to read the raw sensor data from the IMU sensor stick via the I²C bus [73]. A ZigBee module is connected to the microcontroller through a serial port and it sends out joint angle measurements wirelessly. The sensor node is powered by a two-cell Li-Po battery and it can work continuously for one hour. Since multiple joint angle sensor nodes are required for motion capture, ZigBee is used as the communication protocol because it is more energy and cost-efficient compared to other options of wireless protocols such as Bluetooth. The dimension of the joint angle sensor node is 2.5 inches × 1.5 inches × 1 inch and its weight is around 0.2 lbs including the battery. The battery can continuously work for about 30 minutes, and the sampling rate is around 30 Hz.

Since the sensor node is a bit heavy, it might slide down if a velcro is used to attach it to the human body. Therefore the sensor nodes are mounted on a pair of tight sport pants, as is shown in Fig. 2.3b. Another advantage of this setup is that a patient can just put on the pants instead of fumbling with velcros, which shortens the setup time and makes the training more efficient. Note that the sensor box is mounted on the pants while the sensor node and the cover can be moved to change batteries or settings of the IMU.

The second generation employs a commercialized inertial sensor node [74] with a custom design of the packing box, as is shown in Fig. 2.4. A microcontroller is employed to read raw sensor data from the IMU sensor stick through the serial peripheral interface (SPI)
bus [75]. A wireless module is connected to the microcontroller through serial ports to send out measurement packets wirelessly. The sensor node is powered by a Li-Po battery and it can work continuously for 90 minutes. The dimension of the joint angle sensor node is 2 inches \( \times \) 1.4 inches \( \times \) 0.6 inches and its weight is around 0.15 lbs including the battery. The joint angle sensors are attached to human body using velcros, and they can also be firmly screwed to exoskeletons or prostheses.

### 2.3.2 Filtering Algorithm and Joint Rotation Calculation

It is well known that integration of the angular rate measurement from a gyroscope results in drift of angle estimate, and acceleration measurement is often contaminated with high-frequency noise. Both phenomena will make the angle estimate inaccurate. To deal with those problems, a time-varying complementary filter (TVCF) is implemented in the microcontroller for onboard signal processing. The idea of the TVCF is to pass vector measurements from the accelerometer and magnetometer through a low-pass filter, and pass the rate measurements from the gyroscope through a high-pass filter. Cut-off frequency of the TVCF is tuned automatically based on fuzzy logic. TRIAD algorithm is then applied to estimate the orientation based on two vector measurements [76]. More details of the TVCF are available in [77].

To calculate the rotation of one joint, two joint angle sensors are required and they need to be mounted on the two linked ends around this joint. At least five joint angle sensors are thus required to capture the hip and knee joint angles on both sides. In such case, the sampling rate of the overall system can go up to 100 Hz, which is sufficient for capturing human motion. Let us assume the two joint angle sensors are collinear when the joint rotation is zero degree. In this dissertation, the joint rotation is calculated using quaternions. Two
quaternions $q_1$ and $q_2$ are defined as

$$q_1 \equiv \begin{bmatrix} T_1 \\ t_{14} \end{bmatrix}, \quad q_2 \equiv \begin{bmatrix} T_2 \\ t_{24} \end{bmatrix},$$

where $T_i \equiv e^{\sin(\theta/2)} = \begin{bmatrix} t_{i1} & t_{i2} & t_{i3} \end{bmatrix}^T$ and $t_{i4} = \cos(\theta/2)$ for $i = 1, 2$ with $e$ and $\theta$ being the Euler axis and angle, respectively. Raw measurements of the two inertial sensors are quaternions $q_1$ and $q_2$. The quaternion expression of the joint rotation (rotation of sensor 1 with respect to sensor 2) is [78]

$$q_{2\rightarrow1} = q_1 \otimes q_2^{-1} = \begin{bmatrix} \Psi(q_1) & q_1 \end{bmatrix} q_2^{-1},$$

(2.1)

where

$$q_2^{-1} \equiv \begin{bmatrix} -T_2 \\ t_{24} \end{bmatrix}, \quad \Psi(q_1) \equiv \begin{bmatrix} t_{14}I_{3 \times 3} - [T_1 \times] \\ -T_1^T \end{bmatrix}.$$

$[T_1 \times]$ is called the cross product matrix and it can be written as

$$[T_1 \times] \equiv \begin{bmatrix} 0 & -t_{13} & t_{12} \\ t_{13} & 0 & -t_{11} \\ -t_{12} & t_{11} & 0 \end{bmatrix}.$$

After $q_{2\rightarrow1}$ is obtained, it can be converted to the Euler angles for intuitive visualization [79].
2.3.3 Performance Evaluation of the IMU Sensors

In this subsection, a PhaseSpace IMPULSE motion capture system [15] with ten calibrated cameras is employed to verify the accuracy of joint angle estimation. Each camera has 3600×3600 pixels and 480 frame-per-second (FPS) sampling rate. There were at least three markers and one IMU sensor for the torso and each lower limb in order to estimate the hip and knee joint rotations, as is shown in Fig. 2.5. The three markers were placed to be paralleled with the IMU sensor on one limb to minimize the error due to misalignment.

In the experiment, the subject was asked to perform lower limb lifting, forward walking, side walking, and squat. Hip and knee joint rotations of squat are compared from the marker-based motion capture system and IMU sensors, as is shown in Fig. 2.6. It can be confirmed that the estimation results from the two measurement techniques are quite close, which confirms the accuracy of the IMU sensors. It is also clear that the setup of IMU sensors is much simpler than that of the camera-based motion capture system and such advantage plays a very important role in the clinical use with patients.

2.4 Wireless Smart Shoes

In order to better analyze patients’ gaits during walking, a pair of wireless smart shoes is fabricated to measure the GCFs on two feet. Four barometric sensors are employed to measure the GCFs on the toe, the first and second metatarsophalangeal joint (Meta12), the fourth and fifth metatarsophalangeal joint (Meta45), and the heel [8]. Silicone tubes are
coiled into air bladders to connect barometric sensors with a measurement range from 0 to 250 mbar. Each sensor can measure weight up to 200 lbs with a resolution of 0.2 lbs. The air bladders and barometric sensors are calibrated with a load cell. Figure 2.7a shows the air bladders on a shoe pad.

The pressure sensor outputs are read by an Arduino Pro Mini 328 microcontroller through analog input channels and the sensor signals are sent out through a Bluetooth module. The Bluetooth module can smoothly and reliably transmit signals within 200 feet to the receiver, which is enough for normal daily and clinical use. A 9-volt alkaline battery is used to power the smart shoes, and it can work consecutively for 90 minutes. The sampling rate of the smart shoes can go up to 50 Hz with the Bluetooth module. In order to accommodate different human subjects, two pairs of wireless smart shoes are fabricated, one with size 8 and the other with size 12. The pair of size 8 wireless smart shoes are shown in Fig. 2.7b.

2.5 Calculation of Gait Phases and Kinematic Information

Based on the raw measurements, several metrics can be calculated to provide insights for therapists to diagnose patients’ walking problems and develop appropriate training plans.

2.5.1 Gait Phases

Gait phases reveal human walking patterns. There are eight gait phases within a gait cycle [56]: initial contact (IC), loading response (LR), mid-stance (MS), terminal stance (TS),
pre-swing (PS), initial swing (ISw), mid-swing (MSw), and terminal swing (TSw). In this dissertation, the last three swing phases are combined as a swing phase (S). Gait phases can be detected by the GCF patterns from smart shoe measurements, as is shown in Fig. 2.8. Fuzzy logic [8] and HMMs [62] were proposed to infer gait phases during walking in our previous work.

**Gait Phase Detection by Gaussian Mixture Classifier**

One major problem of the fuzzy logic and HMM based approaches is that therapist still needs to input their knowledge for gait detection. For example, the threshold of the fuzzy logic needs to be tuned for different subjects. Therapists have to process a large amount of smart shoe data and make gait phase label first, and then those labeled data are required to train the HMM for future gait detection. It is preferred to employ an unsupervised learning approach so that automatic gait phase detection can be achieved. In this subsection, gait phase detection is performed using a Gaussian mixture model (GMM).

The probability density function of the GMM can be written as

$$p(X|\Theta) = \sum_{i=1}^{M} w_i N(X|\mu_i, \Sigma_i),$$

where $X \in \mathbb{R}^{N}$ is the measurement data from smart shoes. $w_i$ is the mixture weight, and $N(X|\mu_i, \Sigma_i)$ is the component Gaussian densities following

$$N(X|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{N/2} |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (X - \mu_i)^T \Sigma_i^{-1} (X - \mu_i) \right\},$$

where $\mu_i$ and $\Sigma_i$ are the mean and covariance of the $i^{th}$ Gaussian component. The mixture weights satisfy the constraint that $\sum_{i=1}^{M} w_i = 1$. The parameter set that can represent a
CHAPTER 2. A WIRELESS HUMAN MOTION MONITORING SYSTEM FOR GAIT ANALYSIS

GMM is $\Theta = \{w_i, \mu_i, \Sigma_i\}$. The parameter inference of a GMM can be achieved by the expectation maximization algorithm as follows:

$$\hat{w}_i = \frac{1}{T} \sum_{i=1}^{T} p(i|X_t, \Theta), \quad (2.4)$$

$$\hat{\mu}_i = \frac{1}{T} \sum_{i=1}^{T} p(i|X_t, \Theta) X_t,$$  

$$\hat{\Sigma}_i = \frac{1}{T} \sum_{i=1}^{T} p(i|X_t, \Theta) X_t^2 - \hat{\mu}_i^T \hat{\mu}_i, \quad (2.6)$$

where $T$ is the number of data vectors. After obtaining parameters, a posteriori probability of a new incoming data vector belonging to component $i$ is

$$p(i|X_t, \Theta) = \frac{w_i G(X_t|\mu_i, \Sigma_i)}{\sum_{i=1}^{M} w_i G(X_t|\mu_i, \Sigma_i)}. \quad (2.7)$$

Based on this equation, the probability of a new smart shoe measurement data vector belongs to a gait phase can be decided using this GMC. Gait phase for each side is decided using four pressure sensor measurements ($N=4$) and there are six gait phases as mentioned above. As a result, there are six Gaussian components and $M=6$.

2.5.2 Center of Pressure

Center of pressure (CoP) is another way of analyzing the force distributions on the feet during stance phases. It clearly indicates whether a subject steps on the correct locations in a gait cycle. It is also widely used in the analysis of balance and walking stability [80]. Based on the location $(x_i, y_i)$ and force measurement $F_i(t)$ of each sensor, the CoP at time $t$ can be calculated as follows:

$$x_{CoP}(t) = \frac{\sum_{i=1}^{4} x_i F_i(t)}{\sum_{i=1}^{4} F_i(t)}; \quad y_{CoP}(t) = \frac{\sum_{i=1}^{4} y_i F_i(t)}{\sum_{i=1}^{4} F_i(t)}, \quad (2.8)$$

where $x_{CoP}$ and $y_{CoP}$ are the coordinates in the directions of foot width and foot length.

2.5.3 Stride Length and Step Length

Stride length is the distance between two successive placements of the same foot [57], as is shown in Fig. 2.9. It consists of two step lengths, left and right, each of which is the distance
by which the named foot moves forward to the other one. It is common that the two step lengths are similar in a normal gait, but they can be very different in a pathological gait [81].

Given joint angles in the sagittal plane, step lengths can be calculated based on the geometry and lengths of lower limbs. As is shown in Fig. 2.10, step length is calculated at the moment when one foot is touching the ground (heel strike phase) while the other foot is about to leave the ground (pre-swing phase). In this dissertation, this moment is captured when the right hip joint rotation reaches the maximum. It can also be detected when the right heel pressure and the left toe pressure reach the maximum.

Ankle joint rotation does not play an important role in the calculation of step lengths, and
many patients wear the ankle-foot orthoses (AFOs) to support their ankle joints during gait training. Therefore only the hip and knee joint rotations in the sagittal plane are considered and the ankle is assumed to be in its natural position. Furthermore, the foot is treated as a single point at the distal end of the shank. With those assumptions and the geometry in Fig. 2.10, the right step length is calculated as follows

\[ L_r = l_{tr} \sin \theta_{hr} + l_{sr} \sin (\theta_{hr} - \theta_{kr}) + l_{dl} \sin \theta_{hl} + l_{sl} \sin (\theta_{hl} + \theta_{kl}), \]  

(2.9)

and the left step length can be calculated in a similar way. Based on the raw sensor measurements, toe-out angles and stride widths can be calculated as well. They will not be emphasized in this dissertation but briefly introduced in the next subsections.

### 2.5.4 Toe-out Angle

The toe-out describes the angle between the direction of progression and a reference line on the sole of the foot [57]. The toe-out angle can be extracted from the ankle joint rotation in the transverse plane. The toe-out angle can affect the force distribution on the foot and it is therefore very important to keep this angle in the normal range [82].

### 2.5.5 Stride Width

The stride width is the side-to-side distance between the lines of the two feet [57]. The stride width can be measured either at the back of the heel or the center of the ankle. The stride width can be calculated in a similar way to step length. The only difference is one should use joint angles in the frontal plane for calculation.

### 2.6 Design of User Interfaces

In this section, visual feedback is designed based on the measurement data and two different platforms, a laptop and a mobile device such as an iPad.

#### 2.6.1 Visual Feedback on a Laptop

An independent application is developed based on the Windows operation system. After opening this file, a user interface is created, which demonstrates the GCF on each sensing point and the CoP on each foot in real time. An animation is also developed based on the open-source graphics rendering engines (OGRE) [83] so that patients can easily visualize their walking behaviors. Figure 2.11 shows a subject wearing wireless smart shoes and joint angle sensors, together with the user interface on the laptop monitor.
2.6.2 Visual Feedback on an iPad

When a patient walks on the ground, it is inconvenient and potentially unsafe to track his or her walking behaviors by looking at the laptop monitor all the time. To make the system more user-friendly, an application program is developed on the iOS operation system. The processed sensor signals are transmitted from the laptop to the iPad using Bluetooth Low Energy protocol (Bluetooth v4.0). Therefore, a user is able to see the visual feedback on the iPad in real-time. The user interface of the application is shown in Fig. 2.12, where the force distribution, stride length, toe-out angle, and stride width are displayed and updated in real time.

In order to make it easier for patients to get visual feedback from the iPad program, an iPad holder is developed on a belt so that patients or therapists do not need to hold the iPad during the training, as is shown in Fig. 2.13. Patients can rotate the iPad in the holder to find their best view of the screen.

2.7 Experimental Results

In this section, experimental results of one healthy subject and one stroke patient using the wireless human motion monitoring system are shown for gait analysis. Experiments with healthy subjects were conducted in the Mechanical Systems Control Laboratory at the University of California, Berkeley (UC Berkeley), as is shown in Fig. 2.14. The pre-trial with patients was conducted in the William J. Rutter Center at the University of California, San Francisco (UCSF). Healthy subjects and patients were asked to walk straight on a flat ground or a treadmill with the wireless joint angle sensors and smart shoes at different speeds. The healthy subject is male, weighs 140 lbs, and is 5 feet 8 inch tall. The stroke patient is male, weighs 176 lbs, and is 5 feet 10 inch tall.
2.7.1 Experimental Results of A Healthy Subject

To begin with, performance of the GMC is examined by comparing the result with fuzzy logic tuned by the therapist. Figure 2.15a shows the GCF measurement from a healthy subject. The corresponding gait phase detection results using the fuzzy logic and GMC are shown in Figs. 2.15b and 2.15c, respectively. In the fuzzy logic, the gait phase is detected by comparing the fuzzy membership value (FMV), where the FMV of a specific gait phase indicates the likelihood that the user is currently in that phase [8]. In the GMC, the gait phase is detected by comparing the a-posterior probability of each Gaussian component. While there are differences on the gait phase detection, the pattern of detected gait phases are very similar. However, the GMC based approach can achieve automatic detection without
Figure 2.14: Experiment of the wireless human motion monitoring system with a healthy subject

Figure 2.15: Comparisons of gait phase detection algorithms
prior knowledge, which is superior to the rule-based approaches.

Another group of left-side GCFs and detected gait phases of the healthy subject are shown in Fig. 2.16a and Fig. 2.16c. One can observe from Fig. 2.16a that at each step, the heel touches the ground first, then Meta45 and Meta12 touch the ground, and finally the toe touches the ground before the swing phase. Therefore the CoP rolls from the heel to the forefoot. Figure 2.16c shows the FMV of each gait phase, from which it can be confirmed that all the six phases are successfully detected by the fuzzy logic, and the detected phases are sequential because the subject followed a normal gait pattern. Based on the pressure sensor measurements, CoP on the left foot in each gait cycle is calculated and shown in Fig. 2.18a. It is observed that the CoP rolls from the heel all the way to the forefoot, and the CoP trace is closer to the medial side of the foot to maintain balance.

![GCF signals from the left side](image1)

![GCF signals from the right side](image2)

![FMV of each gait phase from the left side](image3)

![FMV of each gait phase from the right side](image4)

Figure 2.16: GCFs and detected gait phases (left: healthy subject, right: stroke patient)

Left hip and knee joint rotations of the healthy subject are shown in Figs. 2.17a and 2.17c. Only measurements in the sagittal plane are shown in this dissertation. The statistics comes from consecutive 50 steps from the healthy subject. For mean values, the hip joint reaches a maximum flexion of around 50 degrees and the knee joint reaches a maximum flexion of approximately 55 degrees. The standard deviation is around 2 degrees at each point in a gait cycle, indicating a very consistent gait pattern for the healthy subject. Note
that there are two local minima of knee flexion in a gait cycle. When the hip joint reaches the maximum flexion, the knee joint reaches the first minimum flexion, which corresponds to the initial contact phase in a gait cycle (0% of the gait cycle). The knee flexion reaches the second minimum when the hip joint flexion is around 20 degrees (40% of the gait cycle), which corresponds to the terminal stance phase in a gait cycle. Those joint angles and force distributions change periodically to generate stable and smooth walking dynamics in a normal gait.

### 2.7.2 Experimental Results of A Stroke Patient

The right-side GCFs and detected gait phases of the stroke patient are shown in Fig. 2.16b and Fig. 2.16d. The right side is the affected side of the patient, which means he suffers abnormal gait patterns mainly on this side due to stroke. As is shown in Fig. 2.16b, although the patient's gait is also repetitive, he tends to press all the four sensors simultaneously instead of rolling from the heel to the forefoot. Moreover, there is some pressure on the toe sensor before heel strike, which indicates the patient does not fully release his toe in the swing phase. The gait phase detection result in Fig. 2.16d is consistent with the GCF pattern. Since the subject cannot support his weight with his heel only, there is no heel strike phase. The lack of pre-swing phase results from the fact that he cannot shift his body weight to the toe right before lifting his foot off the ground. The CoP on the right foot is shown in Fig. 2.18b. Comparing with Fig. 2.18a, the range of CoP is much smaller and the CoP does not start from the heel. This further verifies that one significant problem of the patient is the lack of strong heel strike.
Right hip and knee joint rotations of the stroke patient in the sagittal plane is shown in Figs. 2.17b and 2.17d. While the period of one step of the stroke patient is similar to that of the healthy subject, ranges of both hip and knee joint rotations are much smaller. Moreover, the knee joint rotation pattern is also different because it has an inflection point (60% of the gait cycle) in Fig. 2.17d. Last but not least, the standard deviations of the hip and knee joint angles are larger than those of the healthy subject, which indicates more variations between steps in his gait patterns.

2.8 Chapter Summary

In this chapter, design of the wireless human motion monitoring system was presented. The system included wireless smart shoes to detect gait phases and joint angle sensors to measure the joint kinematics. Several gait parameters, including gait phase and step length, were calculated based on sensor data. User interfaces were developed on a laptop and an iPad to provide visual feedback to patients and therapists. In addition to the fuzzy logic rule based approach, a GMC was applied to achieve automatic gait detection. Experiments were conducted on both a healthy subject and a stroke patient to demonstrate the system’s
capability of distinguishing normal and pathological gaits. In the next chapter, effectiveness of the visual feedback will be addressed by a clinical study with more patients.
Chapter 3

Clinical Study on the Effect of Visual Feedback in Gait Rehabilitation

3.1 Introduction

In the last chapter, a wireless human motion monitoring system was designed and used for analyzing pathological gait and providing visual feedback. Actually many researchers have designed user interfaces to provide different types of feedback to patients during gait training. Vibrotactile feedback was provided to correct the posture of the user during rehabilitation [84]. In [61], visual, audible, and vibrotactile feedback was provided to users on a smartphone. Effect of visual feedback on bilateral standing post-stroke was surveyed in [85] with 78 studies and 214 patients. A review of biofeedback in rehabilitation is available in [86] and it pointed out the importance of verifying the effectiveness of biofeedback in rehabilitation.

In our previous work [87], a user interface was designed on a hand-held display to demonstrate the GCF measurement from the smart shoes and this visual feedback was provided to patients during gait rehabilitation. A pilot study was conducted with seven Parkinson’s disease (PD) patients and the results showed immediate improvement of gait pattern after 20 minutes of gait training. However, the previous visual feedback information was from smart shoes only and the training time was too short to make any clinical conclusions on the effectiveness of gait rehabilitation with visual feedback.

In this chapter, a clinical study is conducted to verify the effectiveness of visual feedback during gait rehabilitation with both stroke and PD patients. Procedures and results of the clinical study is introduced in this chapter. The wireless smart shoes and joint angle sensors were used to measure the gait patterns, and visual feedback was provided to patients on a laptop as well as an iPad. This study was reviewed and approved by the institutional review board (IRB) of the UCSF.
3.2 Procedures of the Clinical Study

3.2.1 Selection of Human Subjects

Adults, males or females, 30-75 years of age, who had suffered a stroke or had been diagnosed with PD for at least a year without other significant health problems except mobility, were eligible for study participation. The subjects needed to be independent in self-care, able to communicate in English and follow instructions, interested in being more mobile and able to rise from a chair and walk without personal assistance for a minimum of 100 feet. All of the subjects had participated in previous research at the UCSF or had received physical therapy in the UCSF Faculty Practice or the UCSF Physical Therapy Health and Wellness Center.

Twenty-six subjects were contacted by phone and met the eligibility screen. These subjects were scheduled for consent and the following baseline testings to confirm eligibility:

- Mental alertness: VA Mental Status Test (≥24) [88] and Beck Depression Scale (<12) [89].
- Independence: Café 40-Functional Independence Scale (≥50%) [90].
- Severity of impairment post Parkinson’s disease: Hoehn and Yahr Scale (between I and III) [91].
- Severity of impairment post stroke: Fugl-Meyer Assessment (≥10) [92].

After the eligibility test, twenty-four subjects were approved to participate in the clinical study.

3.2.2 Gait Training

Procedures of the clinical study is shown in Fig. 3.1. After baseline pre-evaluation, the 24 eligible subjects were randomly assigned to either the control group or the experimental group. The patients in the control group received traditional rehabilitation therapy without any visual feedback, and they relied on the physical therapist to provide guidance for gait corrections. The patients in the experimental group wore smart shoes and joint angle sensors, and visual feedback was provided to the patients via user interfaces on the laptop or the iPad. The data collected from the patients in the experimental group were securely stored in a laptop for further analysis. A post-evaluation session was scheduled for each patient to conduct the same clinical tests as they did in the pre-evaluation for comparisons. A three-month follow-up session was scheduled for each patient to further confirm the effectiveness of rehabilitation training.

Gait training was provided with “one-on-one” supervision by a physical therapist or a research assistant trained by the physical therapist. The training took place in the Physical Therapy Health and Wellness Center at the UCSF, where weights, agility ladders, steps, obstacles, theraband, balls and treadmills were available. The gait training activities were progressive and task-oriented, following the principles of neural adaptation [93] and matched
to the ability and objectives of each subject [94, 95, 96, 97, 98, 99, 100]. The gait training activities integrated exercises for good postural alignment, balance, strengthening of hip abduction, coordination stretching (heel cord, hip, hamstrings) and dual tasking. Mobility training was done indoors and outdoors, over ground and on the treadmill. The gait training activities were similar for subjects in the control and experimental groups, and they are summarized in Tables 3.1, 3.2, and 3.3.

All subjects were scheduled for 12 sessions (90 minutes each session) over a period of 6~8 weeks to adjust for subject vacations and other scheduled commitments. The subjects were also encouraged to walk daily as well as continue usual activities in the community (e.g. social commitments, individual and group exercise programs at home or at a fitness center). One stroke patient in the experimental group suffered unrelated disease and cannot finish all sessions, and is thus dropped out from the analysis.

### 3.2.3 Baseline and Post-training Evaluations

At the baseline and post-training evaluations, the subjects were administered standardized tests for mobility, balance, strength and range of motion (RoM). They were also asked to report the number of falls they experienced the month before admitted and the month during training. The standardized tests are introduced as follows:

- **Mobility**: Timed 10-Meter Walk Test [101] at maximum speed, Six Minute Walk...
Table 3.1: Types of task specific activities integrated into gait training - part I

<table>
<thead>
<tr>
<th>Category</th>
<th>Specific Tasks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transition movements</strong></td>
<td>1. rise from chair with equal weight on affected and unaffected legs</td>
</tr>
<tr>
<td></td>
<td>2. sit down slowly</td>
</tr>
<tr>
<td></td>
<td>3. repetitively and continuously stand up and sit down</td>
</tr>
<tr>
<td></td>
<td>4. partially rising from chair and hold the position with good weight</td>
</tr>
<tr>
<td></td>
<td>distribution to affected side</td>
</tr>
<tr>
<td></td>
<td>5. rise from the chair and quickly walk away</td>
</tr>
<tr>
<td><strong>Coordinated movements</strong></td>
<td>1. tap affected foot on floor: sitting and standing</td>
</tr>
<tr>
<td></td>
<td>2. alternate tapping affected and unaffected foot: sitting and standing</td>
</tr>
<tr>
<td></td>
<td>3. practice bending and straightening the knee: sitting and standing</td>
</tr>
<tr>
<td></td>
<td>4. practice lifting and flexing the hip with knee bent: sitting and standing</td>
</tr>
<tr>
<td></td>
<td>5. practice doing coordinated activities while balancing on affected leg</td>
</tr>
<tr>
<td></td>
<td>(e.g., kick balls to someone else; into net; or against wall)</td>
</tr>
<tr>
<td></td>
<td>6. practice doing coordinated activities while walking</td>
</tr>
<tr>
<td></td>
<td>(e.g., kick balls with affected leg; bounce basketballs while walking)</td>
</tr>
<tr>
<td><strong>Balance activities</strong></td>
<td>1. practice balancing with two feet together, tandem and on one foot</td>
</tr>
<tr>
<td></td>
<td>while on stable, unstable and moving surfaces (e.g., eyes closed and open;</td>
</tr>
<tr>
<td></td>
<td>head turning and nodding; throwing and catching balls)</td>
</tr>
<tr>
<td></td>
<td>2. stand and practice weight shifting without hyper extending affected leg</td>
</tr>
<tr>
<td></td>
<td>in single leg stance</td>
</tr>
<tr>
<td></td>
<td>3. move into double limb partial squat position and hold (e.g., with and</td>
</tr>
<tr>
<td></td>
<td>without back to wall; with and without resistance to leg abduction with</td>
</tr>
<tr>
<td></td>
<td>theraband)</td>
</tr>
<tr>
<td></td>
<td>4. step in place on stable and unstable surfaces eyes open/closed</td>
</tr>
<tr>
<td></td>
<td>5. walk on foam with eyes open/closed</td>
</tr>
<tr>
<td></td>
<td>6. balance on Bosu ball (round side up and round side down) (e.g., eyes</td>
</tr>
<tr>
<td></td>
<td>open and closed; try to throw and catch balls while balancing)</td>
</tr>
<tr>
<td></td>
<td>7. keep balance and weight shift (stepping towards target) while playing</td>
</tr>
<tr>
<td></td>
<td>games (e.g., use two hands and racquet to hit tennis ball; let affected arm</td>
</tr>
<tr>
<td></td>
<td>swing as step forward to roll a ball underhand)</td>
</tr>
<tr>
<td><strong>Walk and dual tasks</strong></td>
<td>1. kick balls</td>
</tr>
<tr>
<td></td>
<td>2. throw balls</td>
</tr>
<tr>
<td></td>
<td>3. bounce balls</td>
</tr>
<tr>
<td></td>
<td>4. sing songs</td>
</tr>
<tr>
<td></td>
<td>5. count backwards out loud</td>
</tr>
<tr>
<td></td>
<td>6. talk and problem solve</td>
</tr>
</tbody>
</table>
### Table 3.2: Types of task specific activities integrated into gait training - part II

<table>
<thead>
<tr>
<th>Category</th>
<th>Specific Tasks</th>
</tr>
</thead>
</table>
| **Stance phase training** | 1. practice standing tall and keeping center of gravity over base of support  
2. shift weight back and forth from affected leg to unaffected leg (stable and unstable support surfaces; as shift weight, let the heel rise and the knee and hip flex to prepare to swing the unweighted leg; step forward with the unweighted leg; weight shift to the forward leg and step back; do not advance forward  
3. facilitate strengthening of gluteus medius (e.g., stand in partial squat position with theraband around legs; push against theraband to strengthen; walk in partial squat position with resistance to hip abduction with theraband; keep balance in partial squat on affected leg only  
4. avoid knee hyperextension  
5. facilitate hip extension at end of stance by staying longer on affected leg during single leg stance  
| **Swing phase training**   | 1. allow knee flexion with initiation of unweighting by the rise of the heel (emphasize the affected side)  
2. practice rolling off the forefoot of affected leg  
3. activate hip flexion and ankle dorsiflexion to initiate swing  
4. decrease circumduction  
5. make step length of affected leg equal to step length of unaffected  
6. with swing of affected leg, step past weight bearing unaffected leg  
7. separate leg (femoral movements) from pelvic movements  
| **Walk**                   | 1. try to minimize hypertonicity and rigidity during walking (may need to use previously prescribed ankle foot orthosis; may need toe spreaders to decrease toe flexion; may need an assistive device to increase stability and confidence)  
2. practice high stepping (over objects; emphasize arm swinging; step over different sized objects separated by different distances)  
3. practice rhythmical stepping; dance steps to music  
4. practice coordinated movements over floor agility ladder  
5. walk backwards, forwards and sideways  
6. walk on a treadmill with and without unweighting (e.g., walk at different speeds; walk with and without a slope; turn around and walk downhill)  
7. walk with ankle weights to increase proprioception  
8. walk to equalize time in both the swing and stance phase on each leg |
CHAPTER 3. CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

Table 3.3: Types of task specific activities integrated into gait training - part III

<table>
<thead>
<tr>
<th>Category</th>
<th>Specific Tasks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stairs</strong></td>
<td>1. step up and down a single stair (emphasize stepping up and with affected leg; increase stair height)</td>
</tr>
<tr>
<td></td>
<td>2. practice forward walking up and down stairs (independent one step at time; reciprocal stepping multiple stairs; reciprocal stepping one flight and more with or without assistive devices)</td>
</tr>
<tr>
<td></td>
<td>3. practice backward walking</td>
</tr>
<tr>
<td></td>
<td>4. practice stepping side ways</td>
</tr>
<tr>
<td><strong>Plyometric activities</strong></td>
<td>1. practice jumping on a Bosu ball</td>
</tr>
<tr>
<td></td>
<td>2. practice jumping over a rope (one foot at a time and then both feet together)</td>
</tr>
<tr>
<td></td>
<td>3. practice jumping up onto Bosu ball</td>
</tr>
<tr>
<td></td>
<td>4. practice step-hop sequence until can skip (with and without holding on)</td>
</tr>
<tr>
<td></td>
<td>5. practice a quick jump step forward</td>
</tr>
<tr>
<td><strong>Strength training</strong></td>
<td>1. walk with ankle weight (walk over ground, walk on treadmill, climb stairs, walk outside)</td>
</tr>
<tr>
<td></td>
<td>2. work on leg press (single and double leg support)</td>
</tr>
<tr>
<td></td>
<td>3. step up high with and without ankle weights</td>
</tr>
<tr>
<td><strong>Flexibility training</strong></td>
<td>1. warm up before gait training (single knee to chest; both knees to chest; stretch hamstrings)</td>
</tr>
<tr>
<td></td>
<td>2. stretch heel cords on stairs and do eccentric exercises (before and after each training session; before and after training on the treadmill)</td>
</tr>
</tbody>
</table>

Test [102], Dynamic Gait Index [103], and Tinetti Gait Assessment [104].

- **Balance**: Timed Up and Go (TUG) Test [105], Five Times Sit to Stand (FTSTS) Test [106], and Berg Balance Scale [107].

- **Strength**: Manual muscle testing using a dynamometer [108]. The force generated for each muscle group was summed to a total score of strength for each leg.

- **Range of Motion**: Measurement using a goniometer [109], with the degrees of motion at each joint in the lower extremity summed to create a total flexibility score for each leg.

### 3.2.4 Statistical Data Analysis

This was a small, randomized clinical trial. Pre, post and post-pre test scores on all dependent measures were described by mean, standard deviation, and effect size. Significance of post-pre test difference scores were analyzed across all subjects, by diagnostic groups and
CHAPTER 3  CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

Table 3.4: Baseline differences following random assignment to control and experimental groups: stroke patients

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Control group (N=7)</th>
<th>Experimental group (N=5)</th>
<th>Test score</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>60.8 (5.4)</td>
<td>66.2 (5.0)</td>
<td>U=24</td>
<td>N</td>
</tr>
<tr>
<td>Subject characters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration with Diagnosis</td>
<td>6.6 (3.6)</td>
<td>10.4 (7.8)</td>
<td>U=32.5</td>
<td>N</td>
</tr>
<tr>
<td>Number of Females</td>
<td>5</td>
<td>3</td>
<td>Z=0.42</td>
<td>N</td>
</tr>
<tr>
<td>Average number of falls</td>
<td>0.57</td>
<td>1.2</td>
<td>U=38</td>
<td>N</td>
</tr>
<tr>
<td>Screening criteria</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stroke Impact Scale</td>
<td>206.6 (44.0)</td>
<td>226.3 (50.4)</td>
<td>U=11</td>
<td>N</td>
</tr>
<tr>
<td>Cafe 40-Functional Independence</td>
<td>151.3 (28.5)</td>
<td>170.0 (40.0)</td>
<td>U=10</td>
<td>N</td>
</tr>
<tr>
<td>VA Mental Status</td>
<td>15.9 (5.6)</td>
<td>27.0 (3.9)</td>
<td>U=13</td>
<td>N</td>
</tr>
<tr>
<td>Fugl-Meyer</td>
<td>14.9 (5.3)</td>
<td>14.5 (5.6)</td>
<td>U=13.5</td>
<td>N</td>
</tr>
<tr>
<td>Beck Depression</td>
<td>5.6 (6.3)</td>
<td>6.1 (2.8)</td>
<td>U=10</td>
<td>N</td>
</tr>
</tbody>
</table>

by control and experimental groups using nonparametric statistics (Matched Pair Wilcoxon Test and Mann Whitney U Test) [110]. All dependent variables were considered independent. Each analysis was tested at $p < 0.05$ (two tailed). Within the stroke group and within the Parkinson’s disease group, differences between the control and experimental subjects were described, but not analyzed for significance due to the small number of subjects.

3.3 Experimental Results

3.3.1 Baseline Evaluations

The mean age of the subjects was 63.5 years with 12 males (5 post stroke and 7 with PD) and 12 females (7 post stroke and 5 with PD). Following grouping by diagnosis and random assignment, there were 12 subjects in the control group (5 with PD and 7 post stroke) and 12 subjects in the experimental group (7 with PD and 5 with stroke). At the baseline evaluation, within the stroke group and the PD group, there were no significant differences in the screening and descriptive variables for subjects assigned to the control or experimental group, which is shown in Table 3.4 and Table 3.5.

3.3.2 Results across All Subjects

In general, the kinematic data and visual feedback were consistent with the diagnosis and command from the therapist. During the swing phase, the clinical observations and the kinematic data both noted foot clearance, presence of ankle dorsiflexion, sequence of weight bearing from the hind foot to the forefoot, ability to roll off the forefoot and initiation of swing with knee flexion and hip flexion. Clinical observations and kinematic data were also
CHAPTER 3  CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

Table 3.5: Baseline differences following random assignment to control and experimental groups: Parkinson’s disease patients

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Control group (N=5)</th>
<th>Experimental group (N=7)</th>
<th>Test score Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age</td>
<td></td>
<td>U=43</td>
</tr>
<tr>
<td>Subject characters</td>
<td>Duration with Diagnosis</td>
<td>11.6 (5.9)</td>
<td>8.7 (4.4)</td>
</tr>
<tr>
<td></td>
<td>Number of Females</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Average number of falls</td>
<td>20.8</td>
<td>31.0</td>
</tr>
<tr>
<td>Screening criteria</td>
<td>Cafe40-Functional Independence</td>
<td>163.6 (19.0)</td>
<td>174.2 (17.4)</td>
</tr>
<tr>
<td></td>
<td>VA Mental Status</td>
<td>29.4 (0.90)</td>
<td>28.1 (1.2)</td>
</tr>
<tr>
<td></td>
<td>Fugl-Meyer</td>
<td>8.8 (1.3)</td>
<td>11.6 (3.6)</td>
</tr>
</tbody>
</table>

consistent during the stance phase relative to symmetry of step length, base of support, time in single limb support (right and left), use of hip extensors beginning with heel strike, and presence or absence of knee hyperextension. It had not been possible for the therapist to interpret differences in the strength of the GCFs except to comment on the difference of the sound as each foot hit the ground.

In this section, the progress of the gait training for all subjects are firstly analyzed using standardized clinical testings in mobility, balance, strength, and range of motion, as introduced in Section 3.2.2 and Table 3.6.

Across all subjects, there were significant post-pre test gains in mobility (10 Meter Walk, step length, Six Minute Walk, Dynamic Gait Index, Tinetti Gait Assessment), Berg Balance, strength (affected and unaffected), and RoM (affected and unaffected) with the effect sizes ranging from 0.38 to 2.0, as is shown in Table 3.6. The subjects post stroke also made significant gains on two of the stroke related screening variables (Fugl-Meyer and Stroke Impact Scale).

Subject signs and symptoms were monitored descriptively during training. The subjects participated in the gait training sessions without exacerbating signs and symptoms, as shown in Table 3.7. The subjects reported low levels of pain at the beginning and end of treatment (effect size from 1.6 to 1.9). Low levels of improvement were reported in sleep (effect size 0.42) and resilience (effect size 0.27). At the beginning of the study, subjects reported an average of 13.7 falls. During the month engaged in gait training, the subjects reported an average of 7.3 falls. The majority of falls were experienced by patients with PD.

3.3.3 Results by Diagnostic Groups

Table 3.8 shows the results within the stroke group. Post training, the subjects in the stroke group made significant gains on all dependent variables except for the Six Minute walk, FTSTS test and the TUG test. For the subjects in the stroke group, the effect sizes for
### CHAPTER 3. CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

Table 3.6: Pre, post and post-pre mean change scores on all dependent variables across all subjects

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Pre score</th>
<th>Post score</th>
<th>Effect size</th>
<th>Test score Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Screening scores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fugl-Meyer</td>
<td>14.7 (5.1)</td>
<td>19.4 (5.9)</td>
<td>1.4</td>
<td>T=0</td>
</tr>
<tr>
<td>VA Mental Status</td>
<td>27.5 (3.5)</td>
<td>27.3 (4.2)</td>
<td>-0.08</td>
<td>T=98</td>
</tr>
<tr>
<td>Café 40-Functional Independence</td>
<td>155.3 (28.9)</td>
<td>155.6 (30.0)</td>
<td>0.02</td>
<td>T=91.5</td>
</tr>
<tr>
<td>Stroke Impact Scale</td>
<td>213.7 (45.0)</td>
<td>222.8 (34.1)</td>
<td>0.37</td>
<td>T=10</td>
</tr>
<tr>
<td>Beck Depression</td>
<td>8.2 (4.8)</td>
<td>8.6 (5.1)</td>
<td>0.14</td>
<td>T=121</td>
</tr>
<tr>
<td><strong>Mobility</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Meter Walk (m/sec)</td>
<td>1.3 (0.6)</td>
<td>1.4 (0.7)</td>
<td>0.48</td>
<td>T=21</td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>0.61 (0.2)</td>
<td>0.63 (0.2)</td>
<td>0.38</td>
<td>T=19</td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>0.62 (0.03)</td>
<td>0.75 (0.2)</td>
<td>0.8</td>
<td>T=15</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>266.0 (134.0)</td>
<td>282.9 (137.8)</td>
<td>0.53</td>
<td>T=55</td>
</tr>
<tr>
<td><strong>Dynamic Gait Index</strong></td>
<td>17.7 (6.2)</td>
<td>19.9 (4.9)</td>
<td>0.55</td>
<td>T=10</td>
</tr>
<tr>
<td><strong>Balance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>12.8 (5.5)</td>
<td>11.8 (5.6)</td>
<td>-0.52</td>
<td>T=115</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>18.4 (23.9)</td>
<td>17.4 (25.1)</td>
<td>-0.22</td>
<td>T=121</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>48.7 (8.2)</td>
<td>50.3 (8.1)</td>
<td>0.55</td>
<td>T=10</td>
</tr>
<tr>
<td><strong>Strength</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>189.1 (75.9)</td>
<td>221.8 (77.8)</td>
<td>2.0</td>
<td>T=0</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>237.4 (45.5)</td>
<td>276.4 (56.6)</td>
<td>1.7</td>
<td>T=5</td>
</tr>
<tr>
<td><strong>RoM</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>545.9 (75.2)</td>
<td>577.9 (47.3)</td>
<td>0.65</td>
<td>T=15</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>567.8 (65.1)</td>
<td>596.3 (48.9)</td>
<td>0.73</td>
<td>T=15</td>
</tr>
</tbody>
</table>

1 The number of subjects for these two significance testings is 11 as they only apply to stroke patients and one stroke patient is dropped from the analysis. Paired Wilcoxon test is applied and the difference is significant at the level of 0.05 if T<19 or T>56. For other testings, the number of subjects for these significance testings is 23. Paired Wilcoxon test is applied and the difference is significant if T<73 or T>202.

Table 3.7: Descriptive changes in signs and symptoms across all subjects

<table>
<thead>
<tr>
<th>Signs and Symptoms</th>
<th>Pre score</th>
<th>Post score</th>
<th>Percentage of difference</th>
<th>Effect size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freezing</td>
<td>9.2 (5.7)</td>
<td>8.9 (5.4)</td>
<td>-3%</td>
<td>-0.10</td>
</tr>
<tr>
<td>Sleep</td>
<td>106.0 (19.9)</td>
<td>113.6 (11.5)</td>
<td>7%</td>
<td>0.42</td>
</tr>
<tr>
<td>Fatigue</td>
<td>52.3 (18.6)</td>
<td>50.4 (18.1)</td>
<td>-2%</td>
<td>-0.08</td>
</tr>
<tr>
<td>Resilience</td>
<td>80.7 (9.3)</td>
<td>82.8 (8.8)</td>
<td>3%</td>
<td>0.27</td>
</tr>
<tr>
<td>Visual analog</td>
<td>1.6 (1.2)</td>
<td>1.9 (2.0)</td>
<td>14%</td>
<td>0.12</td>
</tr>
</tbody>
</table>

1 This only applies the 12 Parkinson’s disease patients.
### Table 3.8: Pre, post and post-pre test gain scores within the group of stroke patients

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Pre score</th>
<th>Post score</th>
<th>Effect size</th>
<th>Test score¹ Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Meter Walk (m/sec)</td>
<td>0.80 (0.52)</td>
<td>0.86 (0.52)</td>
<td>0.50</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>0.47 (0.16)</td>
<td>0.48 (0.17)</td>
<td>0.28</td>
<td>T=10 Y</td>
</tr>
<tr>
<td>Mobility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>0.51 (0.27)</td>
<td>0.59 (0.20)</td>
<td>0.67</td>
<td>T=6 Y</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>182.5 (79.7)</td>
<td>193.0 (85.5)</td>
<td>0.43</td>
<td>T=14 N</td>
</tr>
<tr>
<td>Dynamic Gait Index</td>
<td>15.4 (6.7)</td>
<td>17.3 (5.5)</td>
<td>0.40</td>
<td>T=6 Y</td>
</tr>
<tr>
<td>Balance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>15.8 (6.5)</td>
<td>14.9 (6.6)</td>
<td>-0.35</td>
<td>T=19 N</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>27.2 (31.0)</td>
<td>27.0 (33.9)</td>
<td>-0.05</td>
<td>T=23 N</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>45.0 (9.3)</td>
<td>46.9 (9.0)</td>
<td>0.82</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Strength</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>128.4 (55.7)</td>
<td>159.7 (59.7)</td>
<td>3.4</td>
<td>T=66 Y</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>221.2 (50.9)</td>
<td>270.5 (71.4)</td>
<td>1.9</td>
<td>T=66 Y</td>
</tr>
<tr>
<td>RoM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>521.2 (63.1)</td>
<td>571.2 (18.4)</td>
<td>0.99</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>579.5 (44.3)</td>
<td>603.6 (27.5)</td>
<td>0.50</td>
<td>T=6 Y</td>
</tr>
</tbody>
</table>

¹ Paired Wilcoxon test is applied with N=11. The difference is significant at the level of 0.05 if T<10 or T>56.

The significant differences ranged from a low of 0.28 (step length) to a high of 3.4 (strength, affected side). The PD group made significant gains on all of the dependent variables except gait speed and the TUG test, as is shown in Table 3.9. The effect sizes for the subjects in the PD Group ranged from a low of 0.39 (10 Meter Walk) to a high of 2.14 (strength, unaffected side).

Table 3.10 demonstrates the gait score difference between stroke and PD groups. Mean strength gains on the unaffected side were greater for subjects post stroke compared to subjects with PD. Otherwise there were no significant differences in the gain scores on the other dependent variables for subjects in the stroke group compared to subjects in the PD group. Although not statistically significant, there was a trend for subjects post stroke to experience a higher effect size than subjects post PD in gait speed, Berg Balance, strength (affected side) and RoM (affected side) while subjects in the PD group made greater gains than the stroke group in step length, Six Minute walk, Tinetti Gait Assessment, Dynamic Gait Index, FTSTS test, TUG test, and RoM (unaffected side).

### 3.3.4 Results across the Control and Experimental Groups

Table 3.11 summarizes the post-pre test gain scores for the control and experimental groups. The control group made significant gains on all of the dependent variables except on the FTSTS test and the TUG test. The experimental group made significant gains on all of the dependent variables except the FTSTS test, TUG test, and RoM (affected side). There


### Table 3.9: Pre, post and post-pre test gain scores within the group of PD patients

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Pre score</th>
<th>Post score</th>
<th>Effect size</th>
<th>Test score</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Meter Walk (m/sec)</td>
<td>1.7 (0.27)</td>
<td>1.75 (0.66)</td>
<td>0.08</td>
<td>T=11</td>
<td>N</td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>0.75 (0.13)</td>
<td>0.77 (0.13)</td>
<td>0.44</td>
<td>T=10</td>
<td>Y</td>
</tr>
<tr>
<td>Mobility</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>0.71 (0.20)</td>
<td>0.90 (0.12)</td>
<td>1.0</td>
<td>T=1</td>
<td>Y</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>342.7 (129.4)</td>
<td>364.5 (127.1)</td>
<td>0.60</td>
<td>T=3</td>
<td>Y</td>
</tr>
<tr>
<td>Dynamic Gait Index</td>
<td>19.8 (5.2)</td>
<td>22.3 (2.9)</td>
<td>0.76</td>
<td>T=1</td>
<td>Y</td>
</tr>
<tr>
<td>Balance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>10.0 (2.1)</td>
<td>8.9 (2.3)</td>
<td>-1.0</td>
<td>T=6</td>
<td>N</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>10.4 (10.9)</td>
<td>8.7 (6.6)</td>
<td>-0.39</td>
<td>T=28</td>
<td>N</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>52.2 (5.2)</td>
<td>53.5 (5.8)</td>
<td>0.39</td>
<td>T=3</td>
<td>Y</td>
</tr>
<tr>
<td>Strength</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>244.7 (40.5)</td>
<td>278.7 (38.3)</td>
<td>1.6</td>
<td>T=78</td>
<td>Y</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>252.1 (35.8)</td>
<td>281.7 (41.4)</td>
<td>2.14</td>
<td>T=78</td>
<td>Y</td>
</tr>
<tr>
<td>RoM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>568.6 (80.7)</td>
<td>584.1 (63.9)</td>
<td>0.48</td>
<td>T=6</td>
<td>Y</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>557.1 (80.2)</td>
<td>589.6 (63.2)</td>
<td>1.1</td>
<td>T=3</td>
<td>Y</td>
</tr>
</tbody>
</table>

1 Paired Wilcoxon test is applied with N=12. The difference is significant at the level of 0.05 if T<11 or T>60.

### Table 3.10: Pre, post and post-pre test gain scores between diagnostic groups

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Effect size</th>
<th>Test score</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Meter Walk (m/sec)</td>
<td>0.42</td>
<td>U=45</td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>-0.16</td>
<td>U=59.5</td>
</tr>
<tr>
<td>Mobility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>-0.33</td>
<td>U=88.5</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>-0.17</td>
<td>U=63.5</td>
</tr>
<tr>
<td>Dynamic Gait Index</td>
<td>-0.36</td>
<td>U=64.5</td>
</tr>
<tr>
<td>Balance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>0.65</td>
<td>U=57</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>0.31</td>
<td>U=56</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>0.43</td>
<td>U=52.5</td>
</tr>
<tr>
<td>Strength</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>1.8</td>
<td>U=61</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>-0.25</td>
<td>U=30</td>
</tr>
<tr>
<td>RoM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>0.51</td>
<td>U=39</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>-0.56</td>
<td>U=52</td>
</tr>
</tbody>
</table>

1 Mann Whitney test is applied. The difference is significant at the level of 0.05 if U<33.
CHAPTER 3  CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

were no significant differences in the gain scores between the control and the experimental groups.

Table 3.12 summarizes the post-pre test gain scores for the control and experimental groups within each diagnostic group (stroke and PD). Statistical testing was not performed due to the small number of subjects in each group, however there were trends for the control and the experimental groups. For example, within the stroke group, the effect sizes were greater for the control group compared to the experimental group for gait speed, step length, Six Minute walk, TUG, strength (affected and unaffected) and RoM (affected) while the experimental group performed better than control group on the Tinetti Gait Index, Dynamic Gait Index, FTSTS test, Berg Balance and RoM (unaffected). Within the PD group, the control group showed a trend for achieving greater gains than the experimental group on gait speed, step length, Tinetti Gait Assessment, Six Minute walk, Berg balance, strength (affected and unaffected) and RoM (affected and unaffected). The experimental group showed a trend for making greater gains than the control group on the Dynamic Gait Index, TUG test, and FTSTS test.

3.3.5 Discussion of Clinical Evaluation Results

It is verified from the clinical study that the gait training significantly enhanced mobility, endurance, strength and flexibility of individuals in both the control and experimental groups. The visual kinematic data were generally consistent with the verbal instructions from the therapist. Supervised gait training with visual feedback resulted in similar training performance gains compared to traditional gait training with physical therapists. This finding suggests the potential use of the proposed human motion monitoring system for in-home rehabilitation. The system could provide feedback to the patient to guide independent gait training, and a physical therapist could monitor patient progress remotely. This remote monitoring would allow the therapist to make recommendations about changing the gait training program. In addition, this kinematic feedback system could make it convenient, private, and less expensive for patients to conduct gait training at home.

There are several limitations of the results described in this section. First, the number of subjects in this clinical study was small, particularly for the control and experimental groups. This could have limited the ability to find differences between the control and the experimental groups. Moreover, the gain scores for each criterion were tested for significance at \( p < 0.05 \). This type of analysis assumes independence between each testing outcome, which might not be true although each testing score was measured independently. For example, it is likely that speed, endurance, and step length could interact in the measurement of mobility. Furthermore, although all subjects participated in 18 hours of therapy, the intervention duration ranged from 5-7 weeks to accommodate subject schedules. Last but not least, patients might not be in the same physiological state of their medical condition when performing the pre and post evaluations, and the measurements could not all be administered at exactly the right time. In addition, some evaluation tests required subjective scoring on
Table 3.11: Post and pre test difference scores: control and experimental groups

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Control group</th>
<th>Experimental group</th>
<th>Experimental-Control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Effect size</td>
<td>Test score&lt;sup&gt;1&lt;/sup&gt;</td>
</tr>
<tr>
<td>10 Meter Walk (m/sec)</td>
<td>0.19 (0.37)</td>
<td>0.52</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Mobility Walk (m/sec)</td>
<td>0.02 (0.05)</td>
<td>0.41</td>
<td>T=10 Y</td>
</tr>
<tr>
<td>Mobility Step Length (m)</td>
<td>0.17 (0.21)</td>
<td>0.83</td>
<td>T=6 Y</td>
</tr>
<tr>
<td>Mobility Tinetti Gait Index</td>
<td>17.1 (19.7)</td>
<td>0.87</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Mobility Six Minute Walk (m)</td>
<td>1.8 (4.7)</td>
<td>0.37</td>
<td>T=6 Y</td>
</tr>
<tr>
<td>Mobility Dynamic Gait Index</td>
<td>-0.96 (2.5)</td>
<td>-0.39</td>
<td>T=35 N</td>
</tr>
<tr>
<td>Balance FTST Test (sec)</td>
<td>-1.1 (3.1)</td>
<td>-0.35</td>
<td>T=23 N</td>
</tr>
<tr>
<td>Balance TUG Test (sec)</td>
<td>2.4 (3.3)</td>
<td>0.74</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>Strength A ftected (lbs)</td>
<td>35.0 (14.6)</td>
<td>2.4</td>
<td>T=0 Y</td>
</tr>
<tr>
<td>Strength Unaffected (lbs)</td>
<td>47.2 (25.3)</td>
<td>1.9</td>
<td>T=78 Y</td>
</tr>
<tr>
<td>RoM A ftected (deg)</td>
<td>38.3 (41.5)</td>
<td>0.92</td>
<td>T=3 Y</td>
</tr>
<tr>
<td>RoM Unaffected (deg)</td>
<td>28.6 (44.8)</td>
<td>0.64</td>
<td>T=6 Y</td>
</tr>
</tbody>
</table>

<sup>1</sup> Paired Wilcoxon test is applied with N=12. The difference is significant at the level of 0.05 if T<13 or T>65.

<sup>2</sup> Paired Wilcoxon test is applied with N=11. The difference is significant at the level of 0.05 if T<10 or T>56.

<sup>3</sup> Mann Whitney test is applied. The difference is significant at the level of 0.05 if U<33.
Table 3.12: Post-pre test gain scores within diagnostic groups: experimental and control groups

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Control group</th>
<th>Experimental group</th>
<th>Exp.-Control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gain score</td>
<td>Percentage</td>
<td>Effect size</td>
</tr>
<tr>
<td>Mobility</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Meter</td>
<td>0.08 (0.13)</td>
<td>9.5%</td>
<td>0.61</td>
</tr>
<tr>
<td>Walk (m/sec)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>0.002 (0.05)</td>
<td>2.6%</td>
<td>0.40</td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>0.07 (0.15)</td>
<td>12.8%</td>
<td>0.47</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>21.3 (23.8)</td>
<td>11.7%</td>
<td>0.90</td>
</tr>
<tr>
<td>Dynamic Gait Index</td>
<td>1.7 (5.9)</td>
<td>10.7%</td>
<td>0.29</td>
</tr>
<tr>
<td>Stroke group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>-0.82 (3.2)</td>
<td>-5.2%</td>
<td>-0.26</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>-1.6 (4.1)</td>
<td>-7.8%</td>
<td>-0.40</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>1.7 (2.6)</td>
<td>3.7%</td>
<td>0.67</td>
</tr>
<tr>
<td>strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>33.9 (9.1)</td>
<td>27.4%</td>
<td>3.71</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>60.0 (25.0)</td>
<td>27.1%</td>
<td>2.40</td>
</tr>
<tr>
<td>Rom</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>45.9 (46.6)</td>
<td>8.9%</td>
<td>0.99</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>19.5 (54.2)</td>
<td>3.3%</td>
<td>0.35</td>
</tr>
<tr>
<td>Parkinson’s disease group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Meter</td>
<td>0.35 (0.55)</td>
<td>19.4%</td>
<td>0.64</td>
</tr>
<tr>
<td>Walk (m/sec)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step Length (m)</td>
<td>0.03 (0.06)</td>
<td>3.9%</td>
<td>0.57</td>
</tr>
<tr>
<td>Tinetti Gait Index</td>
<td>0.32 (0.19)</td>
<td>3.1%</td>
<td>0.95</td>
</tr>
<tr>
<td>Six Minute Walk (m)</td>
<td>11.1 (11.7)</td>
<td>54.1%</td>
<td>1.66</td>
</tr>
<tr>
<td>Dynamic Gait Index</td>
<td>1.8 (3.1)</td>
<td>8.7%</td>
<td>0.58</td>
</tr>
<tr>
<td>Balance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSTS Test (sec)</td>
<td>-1.1 (1.3)</td>
<td>-12.2%</td>
<td>-0.85</td>
</tr>
<tr>
<td>TUG Test (sec)</td>
<td>0.3 (0.8)</td>
<td>4.8%</td>
<td>0.39</td>
</tr>
<tr>
<td>Berg Balance</td>
<td>3.4 (4.2)</td>
<td>6.5%</td>
<td>0.82</td>
</tr>
<tr>
<td>Strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (lbs)</td>
<td>36.4 (21.3)</td>
<td>13.8%</td>
<td>1.71</td>
</tr>
<tr>
<td>Unaffected (lbs)</td>
<td>29.9 (13.4)</td>
<td>11.2%</td>
<td>2.23</td>
</tr>
<tr>
<td>RoM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Affected (deg)</td>
<td>27.7 (35.2)</td>
<td>4.9%</td>
<td>0.79</td>
</tr>
<tr>
<td>Unaffected (deg)</td>
<td>41.9 (27.2)</td>
<td>7.5%</td>
<td>1.54</td>
</tr>
</tbody>
</table>

1 For the TUG and FTSTS test, “-” means trend of the experimental group performing better than the control group and “+” means trend of the control group performing better than the experimental group. For all other tests, the signs have the opposite meanings.
CHAPTER 3  CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

Table 3.13: Change of gait parameters based on sensor measurements (SS: smart shoes; JAS: joint angle sensors)

<table>
<thead>
<tr>
<th>Category</th>
<th>Gait Parameters</th>
<th>Source</th>
<th>p-val.(L)</th>
<th>p-val.(R)</th>
<th>Sig.(L)</th>
<th>Sig.(R)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobility</td>
<td>Cadence (steps/min)</td>
<td>SS</td>
<td>2.6 × 10⁻¹¹</td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Double Support Ratio</td>
<td>SS</td>
<td>3.8 × 10⁻⁸</td>
<td></td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>Single Support Ratio</td>
<td>SS</td>
<td>1.2 × 10⁻⁷</td>
<td>4.1 × 10⁻¹¹</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>Stance Phase Ratio</td>
<td>SS</td>
<td>0.08</td>
<td>0.90</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>Step Length (inch)</td>
<td>JAS</td>
<td>0.13</td>
<td>1.4 × 10⁻⁴</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Balance</td>
<td>Max. Force Ratio Difference between Meta12 and 45</td>
<td>SS</td>
<td>0.24</td>
<td>2.6 × 10⁻⁵</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>Min. Force Ratio Difference between Meta12 and 45</td>
<td>SS</td>
<td>0.21</td>
<td>0.89</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Strength</td>
<td>Max. Force Ratio of Heel Strike</td>
<td>SS</td>
<td>8.3 × 10⁻⁶</td>
<td>0.81</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>Max. Force Ratio of Toe Off</td>
<td>SS</td>
<td>6.7 × 10⁻⁵</td>
<td>1.8 × 10⁻⁵</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>RoM</td>
<td>Hip (deg)</td>
<td>JAS</td>
<td>0.23</td>
<td>1.0 × 10⁻³</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>Knee (deg)</td>
<td>JAS</td>
<td>0.75</td>
<td>0.66</td>
<td>N</td>
<td>N</td>
</tr>
</tbody>
</table>

the performance of the subject. This could have introduced uncertainties and inconsistencies regarding the results.

3.4 Statistical Analysis of Training Performance Based on Sensory Data

It is mentioned in Section 3.3.5 that many standardized clinical tests required the therapist to give a score based on graded observations (such as Dynamic Gait Index and Berg Balance Scale). This could produce subjective and potentially inaccurate results. Moreover, it usually takes more than two hours to finish all the clinical evaluation tests, which can be quite tiring and inconvenient. Motivated by these limitations, performance of the training progress was evaluated using sensory data, and findings from one patient are presented in this section.

3.4.1 Proposal of Gait Parameters

Human gait is very complicated and it is difficult to use just a few parameters to get a comprehensive evaluation. However, by constructing some metrics it is easier to detect the gait abnormalities and evaluate the progress made during rehabilitation training.

In Table 3.13, eleven gait parameters are proposed based on the sensor signals. Among them, double support ratio and cadence are comprehensive parameters, which require bilat-
CHAPTER 3. CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

eral information. All the other nine parameters are unilateral, and should be calculated for each side separately [111]. The double support ratio refers to the proportion of time in a gait cycle that both feet are in the stance phase to support the subject, whereas the single support ratio refers to the proportion of time in a gait cycle that only one foot touches the ground while the other is in the swing phase. Stance phase ratio refers to the proportion of time in a gait cycle that one foot is in the stance phase.

The maximum and minimum force differences between the medial (Meta12) and lateral (Meta45) sides of the forefoot in a gait cycle can be calculated as

\[
\begin{align*}
\max_{k \in \mathbb{K}} F_{M12}(k) - F_{M45}(k), \\
\min_{k \in \mathbb{K}} F_{M12}(k) - F_{M45}(k).
\end{align*}
\]

(3.1) (3.2)

These parameters can evaluate the capability of maintaining balance. The \( \mathbb{K} \) refers to the set of indices \( k \) that belong to a gait cycle. Strength is quantified using the maximum force on the heel during heel strike and on the toe during toe off. All balance and strength parameters are normalized by the body weight to make them comparable among different subjects. The RoM is extracted by the maximum difference of joint angles within a gait cycle.

The subjects were asked to walk on a flat ground for at least 50 consecutive steps in their normal walking speeds during the first and last training sessions. It took much less time and effort than the standardized clinical tools to collect data for gait evaluations. Gait parameters were calculated and statistical analysis was conducted correspondingly to examine the distribution and significance. Gait parameters of one stroke patient are shown in the next subsection.

3.4.2 Training Progress Evaluation of a Stroke Patient

The gait parameters of one stroke patient are shown in this subsection to evaluate the progress of training. In Fig. 3.2, the left and right bars of each criterion refer to the results before and after 12 training sessions, respectively. The stroke patient is male, weighs 176 lbs, and is 5 feet 10 inch tall. He was trained in the experimental group.

Figure 3.2a shows the cadence clearly increases, which indicates a higher frequency of walking. Figure 3.2b verifies a significant increase of the double support ratio and a decrease in single support ratios. This indicates the subject gained improved mobility by employing more double support. There are no clear differences in the stance phase ratios. The step lengths on both sides also increase, as is shown in Fig. 3.2c. Based on the three figures, one can conclude improved mobility was achieved for this patient.

In terms of balance, it is demonstrated in Fig. 3.2d that the patient had a clear peak weight shift to the lateral side of the left foot, which is not desirable. The left heel strike and right toe off became stronger, and the toe off of the left side became weaker, as is shown in Fig. 3.2e. Figure 3.2f indicates no clear change of RoM for this patient except a decrease of RoM for the right hip.
Figure 3.2: Gait parameters before and after rehabilitation training for a stroke patient

The statistical significance of the change in each gait parameter was further examined by a two-sample t-test with the p-values summarized in Table 3.13. There were significant changes of cadence, double and single support ratios, step length and maximum force ratio difference of the right side, maximum force ratios of toe off and left heel strike, and right RoM at the level of 0.05. In summary, there were clear improvements on mobility and strength, but no clear improvements in balance and RoM. All findings above were consistent with the self report and clinical measures of the patient. The gait parameters provide more insights to the therapists and help them better schedule the gait training.

3.5 Chapter Summary

In this chapter, clinical effectiveness of the visual feedback brought by the wireless human motion monitoring system was verified by a clinical test with stroke and PD patients. It was demonstrated that patients guided by visual feedback in the experimental group received similar gain score in the standardized clinical tests compared to the patients in the control group under supervised gait training with therapist. This finding suggested good
CHAPTER 3  CLINICAL STUDY ON THE EFFECT OF VISUAL FEEDBACK IN GAIT REHABILITATION

performance of in-home gait training with visual feedback. A therapist could monitor the gait training progress remotely and provide real-time instructions. In addition to the clinical test, eleven gait parameters were proposed to evaluate the change of gait behaviors. This technique was more convenient and accurate, and it also provided more insights to the physical therapist regarding the gait changes of a patient.
Chapter 4

Networked Control of an Assistive Robot: Time Delay Compensation

One major contribution of this dissertation is the high-speed motion control of the assistive robot over the wireless network. In this chapter, one major challenge brought by network media, time delay, will be discussed. This chapter will start with an introduction on the design of wireless infrastructure to support high-speed and real-time control. Two different control approaches will be then introduced to compensate for the negative effect of time delay.

4.1 Introduction

Networked control systems (NCSs) have gained significant attention over the past several decades due to its wide use in telerobotics, process control, vehicle systems, and power systems [112, 113, 114, 51]. The block diagram of a general NCS is shown in Fig. 4.1, where there might be multiple sensors, plants, and actuators. Moreover, not all plants can be observed or controlled. A wireless network is one popular type of network media to transmit sensor and controller signals in a NCS. In this dissertation, emphasis will put on the networked motion control system with only one controlled plant. Compared to traditional wired control systems, wireless NCSs demonstrate great advantages such as enhanced mobility, superior flexibility, and improved safety. However, besides the control challenges existed in the wired control system, a NCS is inherently less reliable than the wired control system due to time delay, packet loss, packet disorder, limited sampling rate, and so forth. Among the aforementioned drawbacks, time delay happens most frequently and it could significantly degrade the performance and even destroy the stability of the NCS.

Since time delay is such an essential and critical problem in a NCS, it has been intensively investigated and various controller schemes have been proposed. To name a few, Smith predictor [115], communication disturbance observer (CDOB) [116, 117], sliding mode control [118], robust control [119], linear quadratic Gaussian (LQG) control [120, 121], and
model predictive control [122] were researched to compensate for time delay. However, most of the approaches presented above focused on stability analysis or stabilizing controller design, and networked tracking controller design is still an open problem that needs to be further studied [123, 124].

In this chapter, design of a high-speed wireless communication protocol is first introduced in Section 4.2 and then two different tracking controller designs are presented. The first controller design is an extension of the LQR control techniques proposed in [120, 121]. Our motivation of this research comes from the fact that desired trajectories of plants can be previewed in many applications. For example, an industrial robot manipulator usually follows a preset trajectory [125]. An autonomous guided vehicle (AGV) always follows a pre-defined path to move materials around a manufacturing facility [126]. A humanoid robot also follows a walking pattern that can be previewed [127]. The information of future reference can be used to design a tracking controller for improved tracking performance because it can help the system increase its effective bandwidth and respond faster to command signals. In the first controller design, the preview control technique [128, 129] is applied to a networked tracking control system with varying time delay that could be longer than one sampling interval. More details are available in Section 4.3.
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

Note that the preview controller design requires an accurate model or measurement of the time delay, which is difficult to achieve in real networked motion control systems. Among all the delay compensation algorithms above, the CDOB [116, 117] has the unique feature that the compensation of time delay does not rely on an accurate model or measurement of time delay. This is appealing because it is very difficult and expensive to measure time delay accurately in many NCSs. The CDOB models time delay as disturbance and employs a disturbance observer (DOB) to cancel the network disturbance, and it has been widely used in bilateral control systems. In a networked motion control system, not only varying and unknown time delay can negatively affect the stability and tracking performance, external disturbance and measurement noise are also inevitable. In order to handle those challenges, a double disturbance observer (DDOB) is developed as the second approach, shown in Section 4.4.

4.2 Design of the RT-WiFi Wireless Protocol

In this section, design of a high-speed and real-time wireless protocol called RT-WiFi is introduced. Supported sampling rate and real-time performance of the current commercialized wireless protocols are summarized in Fig. 4.2. It can be observed that none of the existing wireless protocols support high-speed and real-time wireless communication, which is necessary for high-speed wireless motion control. To validate the benefit of the proposed control algorithm, a networked motion control system with the RT-WiFi [130] is built.
4.2.1 RT-WiFi: Real-time Wireless Protocol for High-speed Networked Control Systems

RT-WiFi is a real-time data link layer protocol designed to support a wide range of NCSs with deterministic real-time data delivery and high sampling rates. Unlike regular Wi-Fi networks which rely on carrier sense multiple access with collision avoidance (CSMA/CA) to avoid collision, RT-WiFi network adopts the time division multiple access (TDMA) mechanism for coordinating the channel access among RT-WiFi devices to provide deterministic real-time data delivery. The TDMA mechanism is achieved by maintaining tight timing synchronization on each device. Since the physical layer of RT-WiFi provides sufficient bandwidth, RT-WiFi supports up to 6 kHz sampling rate. Furthermore, RT-WiFi is designed as a configurable platform to provide great flexibility to a wide range of control applications. Control engineers can base on their needs to customize the design trade-offs among sampling rate, transmission jitter, reliability, and co-existence with regular Wi-Fi networks. An RT-WiFi network has the following three key components:

**RT-WiFi Station:** the RT-WiFi station is a device equipped with IEEE 802.11 compatible hardware and RT-WiFi protocol stack. In a wireless NCS, the system designer connects sensors/actuators to the nearest RT-WiFi station for accessing the wireless network. To guarantee deterministic real-time data delivery, the communication schedule of a station is configured by the network manager when it joins the RT-WiFi network.

**RT-WiFi Access Point:** the RT-WiFi Access Point (AP) connects the RT-WiFi stations. The RT-WiFi network manager resides in the application layer of the RT-WiFi AP, and all data and network management messages are exchanged through the RT-WiFi AP.

**Network Manager:** RT-WiFi network manager [131] is designed to manage the network dynamics and coordinate the TDMA-based communication schedule. To minimize communication jitters in the RT-WiFi network, efficient scheduling algorithms are designed and implemented in the network manager for both static and dynamic link schedule adjustments.
4.2.2 Network Performance

To evaluate the control performance of the proposed algorithm in a real wireless control system, a wireless testbed for motor control was built in the Mechanical Systems Control Laboratory at UC Berkeley. As is shown in Fig. 4.5, it deployed one RT-WiFi AP, one RT-WiFi station, two Arduino Due development boards [132], and a brushless DC motor. Both the RT-WiFi AP and station ran Ubuntu 12.04 operating system, and they were equipped with Atheros AR9280 [133] Wi-Fi cards. To avoid interference from other Wi-Fi traffic, the RT-WiFi network was configured in a 5 GHz channel, where no other Wi-Fi traffic was observed during the experiments. Amplified analog signals were used to control the DC motor. Two Arduino Due boards with Ethernet shields served as the analog-to-digital and digital-to-analog converters, and they were connected to the RT-WiFi station through Ethernet links.

Several software components were developed in this testbed. A controller that implemented the proposed control algorithms in C++ was deployed in the application layer of the RT-WiFi AP. In the application layer of the RT-WiFi station, a packet forwarder was implemented to forward the sensing and control packets between the controller and the Arduino boards. Two socket programs were deployed in the Arduino boards to process the sensing and control data. All the software communication links mentioned above were implemented by User Datagram Protocol (UDP) socket, and each communication packet consisted of 28
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

bytes network and transport layer header and 16 bytes application layer payload. Because of the limited computation power of the embedded processor in the Arduino board, the sampling period of this control loop was configured to be 2048 \( \mu s \).

In the experiment, the wired and wireless time delay was measured in this testbed separately. Because of lacking precise time synchronization mechanisms between the Arduino board and RT-WiFi station, round-trip delay was measured to estimate the one-way delay in the Ethernet link. As Fig. 4.3 shows, the estimated one-way delay in the Ethernet link is stable because the communication traffic was light in the 100 Mbps Ethernet link and one dedicated Arduino board was used for sensing or control traffic respectively.

The end-to-end application layer time delay is reported on the wireless communication link in Fig. 4.4. The wireless time delay was measured by utilizing IEEE 1588 Precision Time Protocol [134] to establish precise clock synchronization between the RT-WiFi AP and station. For this experiment, a periodic TDMA schedule that consisted of 100 time slots was designed, and the size of each time slot was 512 \( \mu s \). A beacon transmission request was scheduled for two time slots in the beginning of the TDMA schedule. For the remaining time slots, feedback and feedforward time slots were interleaved in the TDMA schedule. As is shown in Fig. 4.4a, the delay variation in the feedforward channel (RT-WiFi AP to RT-WiFi station) is regular since RT-WiFi utilizes TDMA to coordinate channel access. It is observed that every one out of 25 packets has latency larger than 1500 \( \mu s \). This phenomenon is resulted from the blocking of a beacon frame in the TDMA schedule. In the TDMA schedule, a beacon frame was scheduled for every 51,200 \( \mu s \). Since the period of the control loop was 2048 \( \mu s \), every one out of 25 control packets was delayed because of beacon transmission.

The feedback delay is shown in Fig. 4.4b. A zig-zag time delay pattern is observed in the feedback channel (RT-WiFi station to RT-WiFi AP) because of loose time synchronization between timers in the Arduino board and the RT-WiFi network. In the RT-WiFi network, a packet is required to arrive at the transmission queue before its scheduled time slot. If the sensing data arrive at the transmission queue of RT-WiFi station periodically, the timing behavior of the feedback channel shall be similar to the feedforward channel. Due to the time drift between the timers in Arduino board and the RT-WiFi station, the sensing packet arrives at the RT-WiFi station sightly later than the designed sampling period. Thus, initially

![Configuration of testbed](image)

**Figure 4.5: Configuration of testbed**
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

the sensing packet spends less time to wait for the next available feedback transmission link in the TDMA schedule. The smallest feedback time delay happens when the sensing packet arrives right before the transmission time slot. As the accumulated drift exceeds the next available transmission time slot, the sensing packet needs to wait for two time slots before it can be transmitted. Thus, a 1000 \( \mu s \) delay jump is observed in Fig. 4.4b periodically.

4.3 Time Delay Compensation with Optimal Preview Control

In this section, a preview control technique is proposed to compensate for time delay with additional feedforward control. This technique relies on the measurement of time delay or an accurate time delay model. The system model is built based on the time delay of the control packet, and an optimal controller is designed to minimize a linear quadratic cost function with preview future reference signals.

4.3.1 System Model with Time Delay

In this section, the following continuous-time single-input-single-output (SISO) system model is considered:

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t - \tau(t)) \\
y(t) &= Cx(t)
\end{align*}
\]  

where \( x(t) \in \mathbb{R}^n \) is the state vector of the system, \( u(t) \in \mathbb{R} \) is the generated controller signal, and \( y(t) \in \mathbb{R} \) is the system output. \( A, B \) and \( C \) are system, input, and output matrices with appropriate dimensions.

To simplify the problem, the following assumptions are made for time delay modeling and controller design:

- Sensors in the system are time-driven, while controllers and actuators are event-driven. The timers of the sensor, controller, and actuator are synchronized.

- Delay in a NCS includes three components, feedback (sensor to controller) channel delay \( \tau^{sc}(t) \), computation delay in the controller \( \tau^{c}(t) \), and feedforward (controller to actuator) channel delay \( \tau^{ca}(t) \). The time-varying round trip delay \( \tau(t) \) is calculated as

\[
\tau(t) = \tau^{sc}(t) + \tau^{c}(t) + \tau^{ca}(t),
\]  

and in this section, \( \tau^{c}(t) \) is neglected as it is not a network-induced delay. It could be categorized into \( \tau^{ca}(t) \) if necessary.

- The networked induced delay is bounded as follows

\[
0 \leq \tau(t) \leq n_0 T_s,
\]
where \( n_0 \) is an integer and \( T_s \) is the sampling time of the system.

- Input \( u(t) \) is piecewise constant in a sampling interval.
- Disturbance and noise are independent of the delay.
- Packet loss and disorder are not considered.
- Initial state of the system is deterministic.

Note that when there is a bounded time delay \( \tau(t) \leq n_0 T_s \), there are at most \( n_0 + 1 \) control inputs acting on the actuator during the sampling interval \([kT_s, (k+1)T_s])\). The changes in \( u(t) \) are assumed to occur at random instants \( kT_s + t^k_i \). It is shown in Fig. 4.6 that \( kT_s + t^k_i \) is the arrival time of control packet \( u_{k-i} \) for \( i = 0, 1, \ldots, n_0 \). If the control packet \( u_{k-i} \) arrives before \( kT_s \), \( t^k_i = 0 \). \( t^k_i = T_s \) if the packet \( u_{k-i} \) does not arrive before \( (k+1)T_s \). Since packet loss and disorder are not considered in this paper, it follows that \( t^k_{i-1} \geq t^k_i \). Adding input and sensor noises yields the following discrete-time system model to be considered:

\[
x_{k+1} = A_x x_k + \sum_{i=0}^{n_0} B_i^k u_{k-i} + B_u w_k
\]

\[
y_k = C x_k
\]

\[
y^m_k = C x_k + v_k
\]

where \( A_x = e^{AT_s} \), \( B_i^k = \int_{t^k_{i-1}}^{t^k_i} e^{A(T_s-t)} dt B \) with \( t^k_{-1} = T_s \) and \( t^k_{n_0} = 0 \), \( x_k = x(kT_s) \), \( y_k = y(kT_s) \), \( y^m_k = y^m(kT_s) \). The system model indicates that \( u_{k-i} \) is applied into the system from \( kT_s + t^k_i \) to \( kT_s + t^k_{i-1} \), where the former is the arrival time of packet \( u_{k-i} \) and the latter is the arrival time of packet \( u_{k-i+1} \). \( u_k \) and \( v_k \) are independent zero-mean Gaussian white noises, and they are also independent of the delay in the system.

To achieve improved tracking performance, the following finite horizon linear quadratic cost function is introduced

\[
J_N = \mathbb{E}_{u_0, \ldots, u_{N-1}} \left[ \sum_{k=0}^{N-1} (e_k^T Q e_k + u_k^T Ru_k) + e_N^T Q_N e_N \right],
\]

where \( Q \) and \( Q_N \) are positive semi-definite, and \( R \) is positive definite. Tracking error is defined as \( e_k = r_k - y_k \), where \( r_k \in \mathbb{R} \) is the reference signal at the \( k^{th} \) time step.

### 4.3.2 Preview Controller Design

**Reference Generator and Augmented System Model**

If future reference signals over a finite horizon are available, tracking performance can be improved by utilizing them. Figure 4.7 shows the assumption on how future reference signals
are given: at time step $k$, only future reference signals up to time step $(k + N_p)$ can be previewed, where $N_p$ stands for the preview horizon. After time step $(k + N_p)$, the reference is modeled as a stochastic signal. The future reference trajectory at the $k^{th}$ step is generated by the following SISO shaping filter [128, 129]:

$$x_{k+1}^r = A_r x_k^r + B_r w_k^r$$

$$r_k = C_r x_k^r$$

where $x_k^r \in \mathbb{R}^t$ is the state of the shaping filter, and $t$ is the order of the shaping filter. $w_k^r \in \mathbb{R}$ is a zero-mean Gaussian white noise with constant variance $W_r$, and it is independent with $w_k$, $v_k$, and time delay. The shaping filter runs $N_p$ time steps ahead of the system model. Therefore, at the $k^{th}$ time step, current and future reference signals $(r_k, r_{k+1}, \ldots, r_{k+N_p-1}, x_{k+N_p}^r)$ are available for the controller design. These reference signals are modeled as the following reference generator:

$$x_{k+1}^d = A_d x_k^d + B_d w_{k+N_p}^r$$

$$r_k = C_d x_k^d$$

where

$$A_d = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & 0 & \cdots & 0 & C_r \\ 0 & 0 & 0 & \cdots & 0 & A_r \end{bmatrix}, \quad B_d = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ B_r \end{bmatrix}.$$
Chapter 4. Networked Control of an Assistive Robot: Time Delay Compensation

![Diagram showing past, future, deterministic, and stochastic futures with time index and current time preview time](image)

Figure 4.7: Representation of the preview control problem

\[ C_d = \begin{bmatrix} \vdots \\ 1 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}^T, \quad x_k^d = \begin{bmatrix} r_k \\ r_{k+1} \\ r_{k+2} \\ \vdots \\ r_{k+N_p-1} \\ x_{k+N_p} \end{bmatrix}. \]

Note that the state of the reference generator \( x_k^d \in \mathbb{R}^{N_p+1} \) consists of current and previewed future reference signals. Output of this reference generator is the reference signal at the current time step.

It should be noted that an autoregressive (AR) model could be represented by (4.11), so theoretically the proposed preview controller could be applied to any reference generated by an AR model [135].

To consider previewed reference signals for controller design, the plant model and reference generator are augmented as follows:

\[
x_{k+1}^a = A_a x_k^a + B_a^k u_k + B_{wa} w_k^a \\
e_k = C_a x_k^a
\]  

(4.13)  

(4.14)

where

\[
x_k^a = \begin{bmatrix} x_k^d \\ x_k \\ u_{k-1} \\ \vdots \\ u_{k-n_0} \end{bmatrix}, \quad w_k^a = \begin{bmatrix} w_k \\ w_{k+N_p} \end{bmatrix}.
\]
CHAPTER 4 NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

\[ A_k^a = \begin{bmatrix} A_d & 0 & 0 & \cdots & 0 & 0 \\ 0 & A_s & B_k^1 & \cdots & B_{k-1}^{n_q} & B_k^{n_q} \\ 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix}, \]

\[ B_k^a = \begin{bmatrix} 0 \\ B_k^{k_n} \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad B_{wa} = \begin{bmatrix} 0 & B_d \\ B_w & 0 \\ 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 \end{bmatrix}, \quad C_a = \begin{bmatrix} C_d^T \\ -C^T \end{bmatrix}^T. \]

Note that \( A_s \) and \( B_k^a \) are the system and input matrices defined in (4.5).

Based on the augmented model (4.13) and (4.14), the cost function (4.8) could be equivalently rewritten as

\[ J_N = \mathbb{E} \sum_{k=0}^{N-1} \left( x_k^a Q' x_k^a + u_k^T R' u_k \right) + x_N^a Q'_N x_N \]

where

\[ R' = \frac{1}{n_q+1} R, \quad Q'_N = C_d^T Q_N C_a + \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & \frac{n_q}{n_q+1} Q_N & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{n_q+1} Q_N \end{bmatrix}, \]

\[ Q' = C_a^T Q C_a + \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & \frac{1}{n_q+1} Q_N & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{n_q+1} Q_N \end{bmatrix}. \]

It is straightforward to verify that \( Q' \) and \( Q'_N \) are positive semi-definite, while \( R' \) is positive definite.

**Design of the Optimal State Controller**

Based on the augmented system model (4.13), (4.14) and cost function (4.15), dynamic programming approach could be applied to get the optimal controller gain using the following theorem:
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

Theorem 4.1. Consider the augmented system (4.13), (4.14), and the cost function (4.15). Optimal controller gain at the \( k \)th time step is given as

\[
L_k = - \left[ R' + \mathbb{E}_{B_k^a} \left( B_a^k P_{k+1} A_a^k \right) \right]^{-1} \mathbb{E}_{A_a^k, B_k^a} \left( B_a^k P_{k+1} A_a^k \right),
\]

where \( P_k \) is solved backwards recursively using the following equation with an initial value \( P_N = Q'_N \)

\[
P_k = L_k^T R' L_k + Q' + \mathbb{E}_{A_a^k, B_k^a} \left[ (A_a^k + B_a^k L_k)^T P_{k+1} (A_a^k + B_a^k L_k) \right].
\]

The optimal cost is given by

\[
J^o = b_0 + x_0^a P_0 x_0^a,
\]

where \( P_0 \) is given by (4.17) and \( b_0 \) is calculated backwards recursively by

\[
b_k = b_{k+1} + \mathbb{E}_{w_k^a} \left( w_k^a B_{wa}^k P_{k+1} B_{wa} w_k^a \right), b_N = 0.
\]

Proof. Based on the Bellman equation, minimum cost at the \( k \)th time step \( J_k^o \) can be expressed recursively as

\[
J_k^o = \min_{u_k} \mathbb{E}_{A_a^k, B_k^a, u_k} \left( x_k^a Q' x_k^a + J_{k+1}^o + u_k^T R' u_k \right).
\]

The boundary condition for the recursion is given as

\[
J_N^o = x_N^a Q'_N x_N^a.
\]

For \( k = N - 1 \), (4.20) can be expressed as

\[
J_{N-1}^o = \min_{u_{N-1}} \mathbb{E}_{A_a^{N-1}, B_a^{N-1}, u_{N-1}^a} \left[ x_{N-1}^a \left( Q' x_{N-1}^a + x_{N}^a Q'_N x_{N}^a + u_{N-1}^T R' u_{N-1} \right) \right].
\]

It should be noted that \( w_{N-1}^a \) is a combination of two independent zero-mean Gaussian white noises. Moreover, \( x_{N-1}^a \) and \( u_{N-1} \) are independent with \( w_{N-1}^a \). Therefore, combining (4.22) with (4.13) gives the following cost function to be minimized:

\[
J_{N-1}^o = \min_{u_{N-1}} \mathbb{E}_{A_a^{N-1}, B_a^{N-1}, u_{N-1}^a} \left[ x_{N-1}^a \left( Q' + A_{a}^{N-1} Q_N A_{a}^{N-1} \right) x_{N-1}^a + u_{N-1}^a \left( B_{wa}^N Q'_N B_{wa} w_{N-1}^a \right) \right] + u_{N-1}^T \left( R' + B_{a}^{N-1} Q_N B_{a}^{N-1} \right) u_{N-1} + 2u_{N-1}^T B_{a}^{N-1} Q'_N A_{a}^{N-1} x_{N-1}^a.
\]
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

Now the cost function (4.22) can be minimized by taking the partial derivative of (4.23) with respect to \( u_{N-1} \) and setting it to zero. Then, the optimal controller gain is obtained as (4.16) with \( P_{k+1} = Q_N \), and optimal cost is obtained as

\[
J_{N-1}^o = b_{N-1} + x_{N-1}^T P_{N-1} x_{N-1},
\]

where \( b_{N-1} = \mathbb{E}_{w_{N-1}} \left( w_{N-1}^T B_w^T Q_N B_w w_{N-1}^T \right) \) and

\[
P_{N-1} = \mathbb{E}_{A_{N-1}^T B_{N-1}^T} \left[ A_{N-1}^T Q_N A_{N-1} + Q' - A_{N-1}^T Q_N B_{N-1} (R' + B_{N-1}^T Q_N B_{N-1})^{-1} B_{N-1}^T Q_N A_{N-1} \right].
\]

Rearranging the terms in (4.25) gives the expression of \( P_{N-1} \) as shown in (4.17). Repeating the same process recursively, the optimal controller gain is obtained and given as (4.16), and the optimal cost is given by (4.18) and (4.19). This completes the proof.

State Estimator Design

It is often inconvenient or expensive to obtain a full state measurement. Moreover, sometimes the measurement is too noisy to be directly used for feedback control. In this subsection, a time-varying Kalman filter is employed to achieve a full state estimate and filter the measurement noise as follows:

\[
\hat{x}_{k+1|k} = A_s \hat{x}_{k|k} + \sum_{i=0}^{n_0} B_k^i u_{k-i}
\]

\[
M_{k+1} = A Z_k A^T + B_w W B_w^T
\]

\[
F_{k+1} = M_{k+1} C^T (C M_{k+1} C^T + V)^{-1}
\]

\[
\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + F_{k+1} (y_{k+1}^m - C \hat{x}_{k+1|k})
\]

\[
Z_{k+1} = M_{k+1} - F_{k+1} C M_{k+1}
\]

where \( \hat{x}_{k|j} \) is the conditional expectation of \( x_k \) given \( Y_{j|m}^m = \{ y_0^m, y_1^m, \ldots, y_j^m \} \). \( Z_k \) and \( M_{k+1} \) are the a-posteriori and a-priori state estimation error covariances defined as

\[
Z_k = \mathbb{E}_{w_0, \ldots, w_k} \left[ \hat{x}_{k|k} \hat{x}_{k|k}^T \right],
\]

\[
M_{k+1} = \mathbb{E}_{w_0, \ldots, w_k} \left[ \hat{x}_{k+1|k} \hat{x}_{k+1|k}^T \right],
\]

where the estimation error is defined by \( \tilde{x}_{k|j} = x_k - \hat{x}_{k|j} \).

It should be noted that since time delay in both feedback and feedforward channels could be longer than one sampling interval, it is possible that \( B_k^1 \) is unknown to the controller. In such case, (4.26) becomes infeasible. To solve this problem, a linear regression model is proposed to estimate the feedforward channel delay in Section 4.3.3.
Chapter 4: Networked Control of an Assistive Robot: Time Delay Compensation

Separation Principle and Stability Analysis

It has been proven in [120, 121] that separation principle holds for the proposed feedback control system with the Kalman filter if $A_k$ and $B_k^k$ in (4.26) are accurately known. Since the previewed reference signals are deterministic and no estimator is required, the separation principle still holds for the preview controller. Combining feedback controller gain (4.16) and Kalman filter (4.26) to (4.30) gives the following controller signal to be implemented:

$$u_k = L_k \hat{x}_k^a,$$

(4.31)

where $\hat{x}_k^a = \begin{bmatrix} x_k^T, \hat{x}_{k|k}, u_{k-1}, \cdots, u_{k-n_0} \end{bmatrix}^T$. A block diagram of the overall control system is shown in Fig. 4.8. Since tracking control is achieved by adding reference feedforward control, it will not affect the stability of the feedback control system. A more detailed stability analysis can be found in [121].

4.3.3 Simulation Study and Discussions

Estimation of Time Delay in the Feedforward Channel

As is mentioned in Section 4.3.2, both feedback and feedforward delays of the control packets $u_k, \cdots, u_{k-n_0}$ need to be available for the Kalman filter to calculate $B_k^k$ in (4.26). Although acknowledgments for some packets could be sent back to the controller about the round-trip delay before the Kalman filter starts to run, some acknowledgments may not be available yet because the delay in each channel could be longer than one sampling interval. Note that most sensing packets in the feedback channel could be delivered within one sampling interval so feedback channel delay is available, but it takes longer to receive an acknowledgment from the actuator (the actuator needs to receive the packet first and then sends out an acknowledgment with the amount of feedforward delay back to the controller). Therefore,
it is more important to estimate the feedforward channel delay. In this subsection, a linear regression model is used to estimate the delay in the feedforward channel based on past delay measurement.

Based on the delay measurement data shown in Fig. 4.4, given a sampling time of 1000 \( \mu s \), feedback channel delay of the \((k - 1)^{th}\) packet \( \tau_{k-1}^{sc}\) and feedforward channel delay of the \((k - 3)^{th}\) packet \( \tau_{k-3}^{ca}\) are guaranteed to be available when the Kalman filter runs at the \(k^{th}\) step. Therefore, those two measurements were chosen as covariates and feedforward channel delay of the current control packet \( \tau_{k}^{ca}\) was chosen as the response variable in the regression model. A physical interpretation of the covariate choice is as follows: \( \tau_{k-1}^{sc}\) is our best knowledge of the current network environment (because it is closer to the current time step) and \( \tau_{k-3}^{ca}\) is our best knowledge of the current network traffic load in the feedforward channel. Based on the least square estimation, the following regression model was built:

\[
\tau_k^{ca} = 354.7 - 0.0983\tau_{k-1}^{sc} + 0.5328\tau_{k-3}^{ca}
\] (4.32)

In comparison, the mean value of the previous feedforward channel delay was used as an estimate of the feedforward channel delay in past literatures such as [120]. Root-mean-square (RMS) errors and coefficient of determination \( R^2 \) are compared in Table 4.1, which indicates a 19.5% reduction of RMS error of the current feedforward delay estimation. Moreover, \( R^2 \) is also increased so that more variation of the delay could be captured by the proposed regression model.
Simulation Setup and Choice of Preview Horizon

In this subsection, the proposed preview control technique is verified by a simulation study. An open-loop stable brushless DC (BLDC) motor was chosen as the plant. The delay measurement shown in Fig. 4.4 was used for simulation study. The sampling rate was set to 1 kHz for precise motion control. Maximum round-trip delay steps $n_0$ in (4.5) was chosen as three considering the delay measurement result and the sampling rate. In the preview controller design, weighting matrices $Q$, $Q_N$, and $R$ in (4.8) were chosen as 100, 100, and 1, respectively. The desired trajectory was generated by the following second-order shaping filter:

$$
\begin{bmatrix}
x_{k+1}^r \\
x_{k+1}^s
\end{bmatrix} =
\begin{bmatrix}
1 & 0.001 \\
-0.016 & 0.9944
\end{bmatrix}
\begin{bmatrix}
x_k^r \\
x_k^s
\end{bmatrix} +
\begin{bmatrix}
0 \\
1
\end{bmatrix} w_k^r
$$

(4.33)

$$
r_k =
\begin{bmatrix}
1 & 0
\end{bmatrix}
\begin{bmatrix}
x_k^r \\
x_k^s
\end{bmatrix}
$$

(4.34)

where $W_r = 50$. This reference generator was designed as a low-pass filter with a cut-off frequency of 5 Hz. The reference trajectory of the motor is shown in Fig. 4.9.

It is very important to decide a reasonable preview horizon for feedforward controller design. It was proposed in [128] that a good estimate of the maximum effective preview horizon $N_{pc}$ can be three times the longest closed-loop plant time constant, which can be
approximated by the settling time with 5% tolerance\textsuperscript{1}. Note that the system and input matrices in (4.13) are time-varying, so the mean values were used for calculation. Using the procedures given in [136], one could get $N_{pc} = 48.5180 \approx 49$. Tracking performance with different preview horizons and the two ways of estimating feedforward delay were obtained and will be compared in the next subsection.

### Simulation Results and Discussions

Performance of the preview controller is highly dependant on the accuracy of the Kalman filter, so the estimation accuracy of the Kalman filter is first examined. The regression model (4.32) was used in the Kalman filter design for feedforward channel prediction. The preview horizon was chosen as $N_p = 50$ considering the $N_{pc}$ calculated in the last subsection. It is shown in Fig. 4.10a that position estimate is accurate even with noise and long time delay. Estimated velocity is smoother than direct position differentiation, as is shown in Fig. 4.10b.

\textsuperscript{1}The closed-loop time constant $a$ is defined in the response $y_t = y_0 e^{-t/a}$ ($y_0$ is the value of the state at time $t$, $y_0$ is the value of the state at time $t = 0$, $a$ is a constant). Therefore, it follows that $y_t \approx 0.05y_0$ when $t = 3a$. Detailed procedure of calculating $N_{pc}$ is given in Section 5.6.2.
Table 4.3: Values of cost function under different preview horizons and delay estimation methods

<table>
<thead>
<tr>
<th>Preview horizon</th>
<th>Linear regression model (4.32)</th>
<th>Mean delay method in [120]</th>
</tr>
</thead>
<tbody>
<tr>
<td>(N_p = 5)</td>
<td>(8.0421 \times 10^4)</td>
<td>(9.9792 \times 10^4)</td>
</tr>
<tr>
<td>(N_p = 10)</td>
<td>(6.2873 \times 10^4)</td>
<td>(7.3378 \times 10^4)</td>
</tr>
<tr>
<td>(N_p = 30)</td>
<td>(5.1573 \times 10^4)</td>
<td>(5.8913 \times 10^4)</td>
</tr>
<tr>
<td>(N_p = 50)</td>
<td>(4.1345 \times 10^4)</td>
<td>(5.3664 \times 10^4)</td>
</tr>
<tr>
<td>(N_p = 60)</td>
<td>(4.0520 \times 10^4)</td>
<td>(5.2225 \times 10^4)</td>
</tr>
</tbody>
</table>

Tracking performance of the proposed controller with preview horizon \(N_p = 50\) is shown in Fig. 4.11, which verifies the good tracking performance under time-varying delay in the NCS. To further examine the tracking performance under various preview horizons and delay estimation techniques, RMS tracking errors and values of the cost function are summarized in Table 4.2 and Table 4.3. It can be concluded from the tables that both RMS tracking errors and cost functions based on regression model are smaller than those from the mean delay method proposed in [120]. Moreover, it could be observed that RMS tracking errors and cost functions become smaller as the preview horizon increases. When the preview horizon goes beyond 50 \((N_{pc})\), the RMS tracking errors and values of the cost function decrease slowly with increased preview horizons.

4.4 Time Delay Compensation Based on Double Disturbance Observers

One major limitation of the preview control based approach is that it needs accurate time delay model or measurement, which might be very difficult to satisfy in real-world applications. In this section, time delay is compensated with double disturbance observers (DDOBs) and this technique does not require any knowledge of time delay. The idea of DDOB is to treat the delay effect as a disturbance input and use a disturbance observer (DOB) to compensate for the negative effect. In order to compensate for both the fictitious network disturbance as well as the actual external disturbance, structure and parameter design of the DDOB is discussed.
4.4.1 System Modeling with Time Delay as Network Disturbance

In this section, the following state-space model of a linear time-invariant (LTI) system with input and output delays is considered:

\[
\begin{align*}
x(k + 1) &= Ax(k) + B (u(k - T_i) + d(k)), \\
y(k) &= C x(k - T_o) + n(k),
\end{align*}
\]

where \( x(k) \in \mathbb{R}^n \) is the system state, \( d(k) \in \mathbb{R} \) is the external disturbance, \( y(k) \in \mathbb{R} \) is the system output, and \( n(k) \in \mathbb{R} \) is the measurement noise. \( T_i \) and \( T_o \) are input and output delays respectively. They may be time-varying but their time indices are omitted in this dissertation. \( A \in \mathbb{R}^{n \times n}, \ B \in \mathbb{R}^{n \times 1}, \ C \in \mathbb{R}^{1 \times n} \) are system, input, and output matrices, respectively. Under zero initial conditions, taking the \( Z \) transformation of (4.35) and (4.36) yields:

\[
\begin{align*}
zX(z) &= AX(z) + Bz^{-T_i} U(z) + BD(z), \\
Y(z) &= Cz^{-T_o}X(z) + N(z).
\end{align*}
\]

Defining \( Y_0(z) = Cz^{-T_o}X(z) \) and assuming no disturbance, the transfer function from \( U(z) \) to \( Y_0(z) \) can be found as:

\[
H(z) = \frac{Y_0(z)}{U(z)} = C(zI - A)^{-1}B z^{-T_i} z^{-T_o} = G(z) z^{-T},
\]

where \( G(z) = C(zI - A)^{-1}B \) is the model of the controlled plant and \( T = T_i + T_o \) is the input-output pure delay in the system. Note that there is no pure delay in \( G(z) \) and the pure delay \( z^{-T} \) is connected to \( G(z) \) in serial. Similar to the case in the continuous time domain [137], network disturbance is defined as:

\[
\begin{align*}
D_n(z) &= U(z) - z^{-T} U(z), \\
d_n(k) &= u(k) - u(k - T).
\end{align*}
\]

With the definition of network disturbance, the state space model (4.35) and (4.36) can be rewritten as:

\[
\begin{align*}
x(k + 1) &= Ax(k) + Bu(k) - Bd_n(k) + Bd(k), \\
y(k) &= Cx(k) + n(k).
\end{align*}
\]

Till now, the original time-delay system has been modeled using a delay-free system with delay-induced network disturbance \( d_n(k) \). In the following subsections, we will investigate how to estimate the network disturbance and compensate for the network disturbance, external disturbance, and measurement noise.
4.4.2 A Double Disturbance Observer Design for Time Delay Compensation

This subsection introduces the structure of the DDOB for robust time delay compensation in a networked motion control system. Based on the control system with CDOB, one more DOB is added into the controller design for disturbance rejection and improved tracking performance.

A Communication Disturbance Observer for Time Delay Compensation

The conceptual block diagram of the control system with a CDOB is shown in Fig. 4.12, where $R(z)$ and $D_{nest}(z)$ are the Z transforms of the reference signal and estimated network disturbance, respectively. $C(z)$ is the baseline controller in the $z$ domain. In the ideal case when there is no disturbance or measurement noise, the desired output of the CDOB is

$$D_{nest}(z) = U(z) - z^{-T}U(z),$$
$$V(z) = CX(z) - z^{-T}CX(z).$$

Since $Y(z) = z^{-T}CX(z)$, one can get

$$W(z) = V(z) + Y(z) = CX(z).$$

The closed-loop transfer function of this system is

$$G_c(z) = \frac{Y(z)}{R(z)} = \frac{C(z)G(z)z^{-T}}{1 + C(z)G(z)}.$$

From (4.47), it is clear that the closed-loop transfer function of this time-delay system is the product of $z^{-T}$ and the transfer function of the corresponding delay-free system. One just needs to design a stabilizing controller for the delay-free system to guarantee the stability of the corresponding time-delay system. By comparing the block diagram in Fig. 4.12 and closed-loop transfer function (4.47) one can verify that the proposed CDOB is equivalent to the Smith predictor [115] when time delay can be accurately measured. However, the
CDOB does not need a delay measurement or model, so it extends the Smith predictor to more practical problems.

Based on the conceptual design of the CDOB, a networked motion control system with the CDOB is proposed in Fig. 4.13. In the block diagram, $n(k)$ denotes the measurement noise and $d(k)$ is the external disturbance, which is different from the network disturbance $d_n(k)$ defined in (4.41). Based on the block diagram, the following input-output relationships can be derived. For simplicity, the variable $z$ in a transfer function is omitted.

\[
G_{yr} = \frac{Y(z)}{R(z)} = \frac{CGz^{-T}}{1+CG_nQ+CG(1-Q)z^{-T}}, \quad (4.48)
\]

\[
G_{yd} = \frac{Y(z)}{D(z)} = \frac{(1+CG_nQ)Gz^{-T}}{1+CG_nQ+CG(1-Q)z^{-T}}, \quad (4.49)
\]

\[
G_{yn} = \frac{Y(z)}{N(z)} = \frac{-CG(1-Q)z^{-T}}{1+CG_nQ+CG(1-Q)z^{-T}}. \quad (4.50)
\]

Transfer functions with different choices of the $Q$ filter are shown in Table 4.4. For now, it is assumed that $G = G_n$. In the original CDOB design, the $Q$ filter is usually chosen as a low-pass filter, which is based on the fact that reference operates in low frequencies and there is no disturbance or noise in the system. Therefore, it is ideal to make $Q = 1$ in low frequencies so that delay effect can be eliminated from the closed-loop characteristic equation and stability can be guaranteed.

As is mentioned before, while the original CDOB design can handle unknown and varying time delay, it does not take disturbance or measurement noise into consideration. There are several possible consequences of directly employing such controllers in a networked motion control system. Based on Table 4.4, the stability cannot be guaranteed in high frequencies as delay effect still occurs in the denominator of $G_{yn}$. Moreover, in low frequencies where disturbance is injected into the system, $G_{yd} \neq 0$. In this case, external disturbance cannot be well rejected.
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

Table 4.4: Closed-loop transfer functions for controllers with CDOB only

<table>
<thead>
<tr>
<th></th>
<th>$G_{yr}$</th>
<th>$G_{yd}$</th>
<th>$G_{yn}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q = 1$</td>
<td>$\frac{CG_{z^{-T}}}{1+CG_{n}}$</td>
<td>$G_{z^{-T}}$</td>
<td>0</td>
</tr>
<tr>
<td>$Q = 0$</td>
<td>$\frac{CG_{z^{-T}}}{1+CG_{z^{-T}}}$</td>
<td>$G_{z^{-T}}$</td>
<td>$\frac{-CG_{z^{-T}}}{1+CG_{z^{-T}}}$</td>
</tr>
</tbody>
</table>

A Double Disturbance Observer Structure for Robustness Enhancement

Motivated by the limitations of the CDOB, a DDOD scheme is proposed and the two observers are designed to handle network disturbance and external disturbance, respectively. The structure of the proposed controller is shown in Fig. 4.14, where there are three blocks in the proposed controller. $C(z)$ is the baseline controller, the lower block has the same structure as in the original CDOB, and the newly added block is a DOB for external disturbance rejection and robustness enhancement [138].

Selection of $Q$ Filters and Stability Analysis

In order to achieve good tracking performance under varying time delay, external disturbance, and measurement noise, the aforementioned three blocks need to be designed carefully. For the two DOBs, the two $Q$ filters, $Q_1$ and $Q_2$, need to be designed. The closed-loop transfer functions of the proposed control systems are derived as follows:

$$
G_{yr} = \frac{Y(z)}{R(z)} = \frac{G (C + G_n^{-1}Q_1) z^{-T}}{1 - Q_1 + G_nQ_2C + Q_1Q_2 + G (1 - Q_2) (C + G_n^{-1}Q_1) z^{-T}} \quad (4.51)
$$

$$
G_{yd} = \frac{Y(z)}{D(z)} = \frac{(1 - Q_1 + G_nQ_2C + Q_1Q_2) G z^{-T}}{1 - Q_1 + G_nQ_2C + Q_1Q_2 + G (1 - Q_2) (C + G_n^{-1}Q_1) z^{-T}} \quad (4.52)
$$

$$
G_{yn} = \frac{Y(z)}{N(z)} = \frac{-G (1 - Q_2) (C + G_n^{-1}Q_1) z^{-T}}{1 - Q_1 + G_nQ_2C + Q_1Q_2 + G (1 - Q_2) (C + G_n^{-1}Q_1) z^{-T}} \quad (4.53)
$$

For both $Q$ filters, the closed-loop transfer functions under unit gain and zero gain are examined in Table 4.5. It is clear that when $Q_1 = 1$ and $Q_2 = 0$, disturbance can be completely rejected and perfect tracking performance can be achieved. On the other hand, when $Q_1 = 0$ and $Q_2 = 1$, noise can be completely canceled. Considering the fact that reference and disturbance are usually in low frequencies, and noise is usually in high frequencies, one can choose $Q_1$ as a low-pass filter and $Q_2$ as a high-pass filter. Multiple objectives, including time delay compensation, reference tracking, disturbance rejection, and noise cancelation, can be achieved in this case.

Stability of the proposed controller can be analyzed by looking at the characteristic equation of the system:
Figure 4.14: Robust controller design in a networked motion control system with DDOBs

**Table 4.5: Closed-loop transfer functions for controllers with DDOBs**

<table>
<thead>
<tr>
<th></th>
<th>$G_{yr}$</th>
<th>$G_{yd}$</th>
<th>$G_{yn}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_1 = 1, Q_2 = 1$</td>
<td>$GG^{-1}_n z^{-T}$</td>
<td>$Gz^{-T}$</td>
<td>0</td>
</tr>
<tr>
<td>$Q_1 = 1, Q_2 = 0$</td>
<td>1</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>$Q_1 = 0, Q_2 = 1$</td>
<td>$CGz^{-T}$</td>
<td>$Gz^{-T}$</td>
<td>0</td>
</tr>
<tr>
<td>$Q_1 = 0, Q_2 = 0$</td>
<td>$CGz^{-T}$</td>
<td>$Gz^{-T}$</td>
<td>$-CGz^{-T}$</td>
</tr>
</tbody>
</table>

\[
T = 1 - Q_1 + G_n Q_2 C + Q_1 Q_2 + Gz^{-T} (1 - Q_2) \left( C + G^{-1}_n Q_1 \right) = 0. \quad (4.54)
\]

From (4.54) it is true that in the low-frequency case where $Q_1 = 1$ and $Q_2 = 0$, $T = Gz^{-T} (C + G^{-1}_n) = 0$. In high-frequency case where $Q_1 = 0$ and $Q_2 = 1$, $T = 1 + G_n C = 0$. Therefore it is confirmed that in both cases negative effect of time delay can be eliminated and stability can be achieved with a stabilizing baseline controller designed in the delay-free case.

It is well known that an accurate system model usually cannot be obtained in controller design. Moreover, the Q filters cannot have a perfect unit or zero gain in real implementation. However, all the analysis above assumes an accurate model with perfect implementation of Q filters, which is not practical. Therefore, it is important to analyze the robust stability of this system. The modeling uncertainties are assumed to satisfy the following equation

\[
G = G_n (1 + \Delta W_m), \quad (4.55)
\]
where $\Delta$ is a stable transfer function satisfying $\|\Delta\|_\infty \leq \delta$ and $W_m$ is a transfer function. The DDOB block diagram in Fig. 4.14 can be reformulated as is shown in Fig. 4.15, where

$$K_1 = \frac{C + G_n^{-1}Q_1}{1 - Q_1 + (C + G_n^{-1}Q_1)G_nQ_2},$$

$$K_2 = \frac{K_1G_n(1 - Q_2)}{1 + K_1G_n(1 - Q_2)}.$$

Based on small gain theorem [139], the condition for robust stability can be derived as follows

$$\|K_2W_m\|_\infty < 1.$$  \hspace{1cm} (4.56)

In the next subsection, robust stability of the proposed control system will be examined.

### 4.4.3 Performance Analysis and Simulation Results

The model of a brushless DC motor is used in analysis, simulations and experiments:

$$G_n = \frac{0.0143z + 0.0142}{(z - 1)(z - 0.9725)}.$$  \hspace{1cm} (4.57)

Sampling time of the system is selected as 2.048 ms to make it consistent with RT-WiFi design shown in Section 4.2. Cut-off frequencies of $Q_1$ and $Q_2$ are chosen as $100$ rad/s and $1000$ rad/s respectively. Time delay measurements shown in Fig. 4.3 and Fig. 4.4 are used for simulation but they are unknown to the controller.
Design of the Baseline Controller

In the proposed robust networked motion control system, the baseline controller plays an important role in the transient performance. It can be designed without considering the delay effect. In this section, a linear quadratic (LQ) controller is designed based on the model of the DC motor and it is implemented as a proportional-derivative (PD) controller. The optimal gain was calculated to be $K_p = 0.6023$ and $K_d = 0.0105$. To check the effect of the baseline controller, various PD control parameters were chosen around the optimal gain and the corresponding closed-loop Bode plots are shown in Fig. 4.16. It can be observed that as the PD control gain increases, a resonance can occur in the $G_{yr}$ and $G_{yd}$ while better disturbance rejection can be achieved in low frequencies. Moreover, large derivative gain makes the controller very sensitive to measurement noise and leads to oscillations in the output.

Verification of Robust Stability

Before the proposed controller is applied in simulations and experiments, the robust stability conditions (4.56) are examined. Based on the system identification results of the DC motor, a $W_m$ can be designed to be an upper bound of the modeling uncertainties and a sufficient
CHAPTER 4  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: TIME DELAY COMPENSATION

Figure 4.17: Magnitude of $K_2$, $W_m^{-1}$, and modeling uncertainties

Table 4.6: Comparison of RMS tracking errors with different controllers in simulations (deg)

<table>
<thead>
<tr>
<th></th>
<th>Double DOBs</th>
<th>CDOB Only</th>
<th>PD Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Disturbance</td>
<td>0.153</td>
<td>1.231</td>
<td>1.017</td>
</tr>
<tr>
<td>With Disturbance</td>
<td>0.159</td>
<td>20.038</td>
<td>1.246</td>
</tr>
</tbody>
</table>

condition of (4.56) can be

$$\|K_2\|_\infty < \|W_m^{-1}\|_\infty.$$  (4.58)

Therefore, practically one can check whether the magnitude of $K_2$ is smaller than that of $W_m^{-1}$ in all working frequencies [140]. Magnitude of $K_2$, $W_m^{-1}$, and modeling uncertainties for the frequencies from 0.1 Hz to 10 Hz are compared in Fig. 4.17, and it can be clearly seen that at all working frequencies $K_2$ stays below the $W_m^{-1}$. As a result, robust stability is achieved in this design.

Simulation Results with DDOBs and CDOB

In order to verify the performance improvement brought by the new structure, comparisons are made between the tracking performance of DDOBs and CDOB. The reference signal was chosen to be a sinusoidal wave with a magnitude of 10 degrees and frequency of 1 Hz. The disturbance was chosen as a sinusoidal signal with a magnitude of 0.1 volt and a frequency of 0.5 Hz. The optimal PD control gain was applied to both controllers and the tracking performance is shown in Fig. 4.18. Figure 4.18a demonstrates that proposed DDOBs work better than the NCS with CDOB when there is no disturbance. More importantly, when disturbance is injected into the system, the proposed algorithm can reject the disturbance while the original CDOB amplifies the disturbance and causes large tracking errors, as is shown in Fig. 4.18b. RMS errors are shown in Table 4.6, from which one can draw the same conclusion.

This result is not surprising by checking the closed-loop transfer functions of the original CDOB and the proposed DDOB. From Table 4.4 it is clear that the magnitude of disturbance is multiplied by the gain of the plant in low frequencies ($Q = 1$). Since there is a large DC gain of our plant in low frequencies, the disturbance is significantly amplified. On the contrary,
based on Table 4.5 and Fig. 4.16b it can be confirmed that disturbance is greatly attenuated in low frequencies by the DDOB, which results almost the same tracking performance with or without disturbance.

4.4.4 Experimental Study

Experimental Setup

Based on the system integration, several experiments were conducted to examine the performance of the proposed algorithm. As was mentioned in Section 4.2, the DDOB algorithm was implemented in the RT-WiFi AP. The reference signals were chosen to be a sinusoidal wave with a magnitude of 10 degrees and frequency of 1 Hz, which was the same as the settings in the simulations. Sampling time of the system is 2.048 ms as illustrated in Section 4.2.2. Based on the simulation results, it is clear that direct implementation of the original CDOB will lead to large errors due to the amplification of disturbance. Therefore, the CDOB was modified by changing the Q filter to a high-pass filter. Based on Table 4.4 one can easily verify that in low frequencies this is nothing but a PD controller. In the meantime, the only difference between the modified CDOB and proposed DDOB is the introduction of the additional DOB block for disturbance rejection and noise cancelation. In this case, tracking performance is comparable and more insights will be gained. Both the DDOB and modified CDOB structures are employed with the same PD control gains as in simulations.
Figure 4.19: Experimental results with different control structures and baseline controllers

Table 4.7: Comparison of RMS tracking errors with different controllers in experiments (deg)

<table>
<thead>
<tr>
<th></th>
<th>Double DOBs</th>
<th>Modified CDOB</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_p = 0.4, K_v = 0.01$</td>
<td>0.7883</td>
<td>0.8470</td>
</tr>
<tr>
<td>$K_p = 0.6, K_v = 0.01$</td>
<td>0.6303</td>
<td>0.7417</td>
</tr>
<tr>
<td>$K_p = 0.8, K_v = 0.01$</td>
<td>0.4857</td>
<td>0.9060</td>
</tr>
<tr>
<td>$K_p = 0.8, K_v = 0.02$</td>
<td>0.9993</td>
<td>1.6853</td>
</tr>
<tr>
<td>$K_p = 1, K_v = 0.01$</td>
<td>0.6231</td>
<td>1.1353</td>
</tr>
</tbody>
</table>

and tracking performance is compared.

**Experimental Results**

Experimental results of the two different control schemes with the same baseline controllers are compared in Fig. 4.19. It is clear that the proposed controller yields less oscillations and magnitudes of errors are also smaller in both cases. Moreover, increasing the proportional gain in the baseline controller helps further reduce the tracking errors. However, the PD gain cannot be increased too much because this will amplify the measurement noise and lead
to increased tracking errors. It is also noticed in Fig. 4.19a that the tracking errors of the DDOBs are larger in experiments than in simulations. This is a consequence of several issues including modeling uncertainties and packet loss in the experiments. Table 4.7 summarizes the RMS tracking errors with the two control schemes and various baseline controllers, from which one can confirm the performance of the DDOBs in compensation for time delay and attenuation of disturbance and noise.

4.5 Chapter Summary

In this chapter, control algorithms for time delay compensation in a networked motion control system were developed, aiming at applications to the robotic assistive device. Before controller design, design and system integration of a new wireless communication protocol, RT-WiFi, was illustrated and a wireless motion control testbed was built. Measurement of time delay was analyzed and used for controller design. The first algorithm, preview control, made use of the time delay measurement to build the system model that incorporated the effect of time delay, and an optimal controller was designed to minimize the cost function of future tracking errors and control effort over a finite horizon. Simulation results were provided to validate the performance of the preview controller design. Despite the good tracking performance of the preview controller, it required an accurate delay model or measurement, which was usually not unavailable in controller design. In order to overcome this limitation, a double disturbance observer (DDOB) approach was presented, and it modeled the delay effect as an equivalent system disturbance. Two disturbance observers were proposed to deal with the virtual disturbance as well as the actual external disturbance and sensor noise. Simulation and experiments were conducted to verify the performance of the proposed controller design.
Chapter 5

Networked Control of an Assistive Robot: Packet Loss Compensation

In this chapter, another challenge brought by the network media, packet loss, is discussed. Two different approaches are proposed to handle the random packet loss during wireless communication. The proposed algorithms are verified by both simulations and experiments with the robotic assistive device.

5.1 Introduction

As is mentioned in the last chapter, a wireless NCS is inherently less reliable than the traditional wired control system. One critical problem in a wireless network is packet loss, which happens randomly in both feedback and feedforward channels. Packet loss degrades the performance of a NCS and can even destroy the stability of the system, which may adversely compromise the safety of the operator. Therefore, control algorithms for a wireless tracking control system, which can guarantee stability and performance of the system in the presence of packet loss, are required.

In order to compensate for the negative effect of packet loss, modeling, analysis, and control of the NCS have been heatedly discussed in recent years. To model packet loss, Bernoulli variables [141] and Markovian jumping parameters [142] were widely used. Stability analysis and stabilizing controller design were discussed in [52]. $H_\infty$ control [142], generalized predictive control (GPC) [122], and modified linear quadratic Gaussian (LQG) control [141] were proposed to achieve improved closed-loop performance. Among these methods, $H_\infty$ controllers were typically designed by solving optimization problems in the form of algebraic Riccati equations or linear matrix inequalities (LMIs). In GPC, future output was estimated based on the system model and control inputs. A cost function of future tracking errors and control inputs was minimized in each time step online to get the optimal controller. Modified LQG control [141] introduced a packet loss model into the optimal controller and Kalman filter design.
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

In this chapter, a compact rotary series elastic actuator (cRSEA) [140] is briefly introduced as the robotic assistive device in the NGRS. Packet loss in the feedback and feed-forward channels are then modeled as two independent Bernoulli processes for networked motion control. As the first approach, the modified LQG (MLQG) control [141] is enhanced by adding a disturbance observer as an internal loop compensator for robustness. Simulation results are presented and experiments are conducted with the a human subject wearing the assistive device [143].

The second approach is based on the preview control technique. Preview control was first introduced by Sheridan in 1966 [144]. Discrete LQ preview tracking control was formulated by Tomizuka in the 1970s [128]. In the subsequent 30 years, $H_2$ or LQG preview control, continuous preview control, and $H_\infty$ preview control [145, 146] were proposed. Preview control can be considered as a natural extension of LQG control, but it has not been investigated for packet loss in a NCS yet. In this chapter, the discrete preview control technique is modified by introducing Bernoulli packet loss model into the cost function, and the optimal gain is obtained by dynamic programming [136]. A Kalman filter is also modified by including the packet loss model for full state estimation and state feedback control. From this point of view, the proposed method can also be considered as an enhancement of the MLQG control technique in [141].

5.2 A Compact Rotary Series Elastic Actuator

In the proposed network-based rehabilitation system, a compact rotary series elastic actuator (cRSEA) is applied to provide assistive torque to the user’s knee joint. The cRSEA employs the rotary series elastic mechanism which utilizes a torsional spring between a human joint and an actuator. In the cRSEA, a geared DC motor is used as an actuator while a worm gear set and spur gears are used to amplify the torque generated by the motor. Figure 5.1 shows the cRSEA installed on an orthosis for the knee joint and its mechanism. The installed spring acts as a torque sensor and a torque transmitter. The desired assistive torque, $\tau_{Ad}$, is transmitted as follows (time indices are omitted here):

$$\tau_{Ad} = k(\theta_{Md} - \theta_H) \quad (5.1)$$

where $k$ is the spring constant, $\theta_H$ is the human joint angle, and $\theta_{Md}$ is the desired motor angle. Then, desired motor angle is calculated,

$$\theta_{Md} = \frac{\tau_{Ad}}{k} + \theta_H \quad (5.2)$$

The desired motor angle is precisely controlled to have an appropriate spring deflection for accurate transmission of the desired assistive torque, i.e. for force mode control. The DC motor can be modeled as a second-order linear system and human-robot interactions produce disturbance into the motor control system. For more details of the cRSEA, see [140].
5.3 Packet Loss Modeling

In this section, modeling of packet loss is first discussed. Since packet loss happens randomly in a wireless network, it can be modeled using a stochastic method. Two independent Bernoulli variables with successful transmission probabilities are used to indicate successful or unsuccessful transmissions at the $k^{th}$ time step as follows:

$$\lambda_k = \begin{cases} 1, & \text{with probability of } \lambda \\ 0, & \text{with probability of } 1 - \lambda \end{cases}$$

$$\rho_k = \begin{cases} 1, & \text{with probability of } \rho \\ 0, & \text{with probability of } 1 - \rho \end{cases}$$

where $\lambda$ and $\rho$ are the probabilities of successful transmission in controller-actuator and sensor-controller channels, respectively. In real applications, $\lambda$ and $\rho$ can be achieved by experiments [130]. In this section, $\lambda_k = 1$ means the actuator receives the $k^{th}$ control packet from the controller, otherwise we model $\lambda_k = 0$. Similarly, $\rho_k = 1$ means the controller receives the $k^{th}$ sensing packet from the sensor, otherwise we model $\rho_k = 0$. If a measurement packet is lost, a Kalman filter can be used to estimate the output in the current time step [141]. If a controller packet is lost, two different strategies, the zero-input method and the hold-input method, have been considered to deal with packet loss in most literature [147, 141, 148]. The zero-input method is formulated as follows:

$$x_{k+1} = Ax_k + Bu_k^a + B_w w_k$$

$$u_k^a = \lambda_k u_k^c$$

where $u_k^c$ is the generated control command from the controller. Note that if the packet is successfully delivered, then $u_k^a = u_k^c$, otherwise, $u_k^a = 0$. 

Figure 5.1: Compact rotary series elastic actuator (cRSEA) and the mechanism [140]
 CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

The hold-input method is formulated as follows:

\[ x_{k+1} = Ax_k + Bu_k + B_w w_k \]  \hspace{1cm} (5.7)

\[ u_k = \lambda_k u_k^c + (1 - \lambda_k) u_{k-1}^c \]  \hspace{1cm} (5.8)

In this method, if the control command is not successfully delivered, then the previous control command is used, i.e., \( u_k = u_{k-1}^c \), otherwise, \( u_k = u_k^c \).

Intuitively, the hold-input method seems to provide better performance than the zero-input method since the true control input is likely to be close to the previous value. As pointed [148] and [141], however, none of the two control schemes can be claimed to be superior to the other, even in simple scalar systems. Moreover, hold-input strategy usually requires additional storage in the actuator for storing past controller signals, which increases the cost and complexity of the system. Thus, the zero-input strategy is used for system modeling and controller design in this thesis.

To summarize, given the packet loss model in (5.3) and (5.4) with the zero-input strategy, the following single-input-single-output (SISO) wireless control system is formulated:

\[ x_{k+1} = Ax_k + Bu_k + B_w w_k \]  \hspace{1cm} (5.9)

\[ u_k = \lambda_k u_k^c \]  \hspace{1cm} (5.10)

\[ y_k = C x_k \]  \hspace{1cm} (5.11)

\[ y_k^m = \rho_k C x_k + v_k \]  \hspace{1cm} (5.12)

where \( x_k \in \mathbb{R}^n \) is the state vector of the system, \( u_k^c \in \mathbb{R} \) is the generated controller signal from the controller, and \( u_k \in \mathbb{R} \) is the actual controller signal implemented to the actuator. \( y_k \in \mathbb{R} \) is the system output and \( y_k^m \in \mathbb{R} \) is the noisy measurement of output. \( A, B \) and \( C \) are system input, output, and output matrices with appropriate dimensions. \( w_k \in \mathbb{R} \) and \( v_k \in \mathbb{R} \) are independent zero-mean Gaussian white input and measurement noises with constant covariances \( W \) and \( V \), respectively.

### 5.4 Data Transfer via the Internet

In the proposed NGRS, the high-level controller (host controller) or a physical therapist sends a desired assistive torque command to the local computer based on the received patient’s information. The tele-communication between the local host controller (patient side) and the host controller (therapist side) is achieved by the Internet.

In this system, transmission control protocol (TCP) is used as in the usual Internet communication. TCP is known as a more reliable data transmission protocol than UDP because TCP uses an acknowledgment scheme to verify the signal is correctly delivered. UDP might be claimed as a better protocol than TCP for the tele-operation system as it has been successfully applied to tele-operation systems [149, 150]. However, TCP is employed in the proposed system since reliability is the first priority in this application. In TCP, if the
sender does not receive acknowledgements before the specified time, the packet is resent [151].
Since the received signal is used as the reference of the rehabilitation device, the resent, thus delayed, signal cannot be used as the reference in the local host controller. In the proposed system, packet buffer, which is responsible for maintaining the queue of previous values, is utilized in both the local host controller and the host controller so that the delayed packet can be used. By using the packet buffer, time delay may exist according to the size of the packet buffer, but the desired assistive torque command can be insulated from unexpected fluctuations in network traffic or read/write rates in the programs.

Preliminary experimental results are shown in Fig. 5.2. In this experimental setup, two computers were connected via the Internet, and the Internet communication programs by National Instrument (NI) LabVIEW were implemented in each computer. The size of the packet buffer could be set in each program. As shown in Fig. 5.2a, the transmitted trajectory without a packet buffer is not smooth due to the packet loss even though some of the packet delivered in real-time. The transmission with a packet buffer shows the smooth trajectory with a little time delay as in Fig. 5.2b. In the actual experiments, 200 packets are maintained in the buffer with 1 kHz transmission rate, which results in a maximum 0.2 second delay. In the experiment, 0.16 second delay was observed. Since the motion speed in rehabilitation treatments is usually slow, the smooth trajectory with a little time delay is adopted by
utilizing appropriate size of packet buffer. Also, the time delay in the Internet does not cause a stability issue of the system because only the reference signals are delivered by the Internet. If the time delay is expected to be large due to inferior Internet environment, the size of the packet buffer can be increased to stack the delayed packet as long as the time delay does not significantly disturb the rehabilitation treatment.

5.5 Modified LQG Control for Packet Loss Compensation

In this section, a MLQG control technique is employed to compensate for the negative effect of packet loss in the wireless motion control of the crSEA. Based on the packet loss model proposed in the last subsection, the possible packet loss is considered in the optimal controller and estimator design. Since the crSEA works with human subjects directly, significant modeling uncertainties and external disturbance can be expected. Moreover, it is shown in this section that packet loss effect can also be treated as external disturbance. A DOB is added as an internal loop compensator to achieve improved robustness and disturbance rejection. Both simulation and experimental results are demonstrated in this section to verify the performance of the proposed algorithm.

5.5.1 Controller Design

Optimal State Feedback Controller Design

The optimal control input of the zero-input strategy can be calculated by the standard dynamic programming approach. Consider the following quadratic performance index [141]:

\[
J_N = \mathbb{E}_{\lambda_0, \ldots, \lambda_{N-1} \atop u_0, \ldots, u_{N-1}} \left[ x_N^T S x_N + \sum_{k=0}^{N-1} \left( x_k^T Q x_k + \lambda_k u_k^c R u_k^c \right) \right]
\]  

(5.13)

where \( S \) and \( Q \) are positive semi-definite matrices and \( R \) is a positive definite matrix. By minimizing the performance index, the optimal control gain, \( L_k \) is obtained as follows:

\[
L_k = [R + B^T P_{k+1} B]^{-1} B^T P_{k+1} A
\]  

(5.14)

where \( P_k \) is obtained recursively by the modified Riccati equation with the initial value \( P_N = S \) as follows:

\[
P_k = A^T P_{k+1} A + Q - \lambda A^T P_{k+1} B \left( R + B^T P_{k+1} B \right)^{-1} B^T P_{k+1} A
\]  

(5.15)
The system states are estimated by the Kalman filter as follows [147, 141, 148]:

\[
\begin{align*}
\hat{x}_{k+1|k+1} &= \hat{x}_{k+1|k} + \rho_{k+1} F_{k+1} (y_{k+1} - C \hat{x}_{k+1|k}) \\
\hat{x}_{k+1|k} &= A \hat{x}_{k|k} + \lambda_k B u_k \\
F_{k+1} &= M_{k+1} C^T [C M_{k+1} C^T + V]^{-1} \\
M_{k+1} &= A Z_k A^T + B w B^T \\
Z_{k+1} &= M_{k+1} - \rho_{k+1} F_{k+1} C M_{k+1}
\end{align*}
\]

(5.16)  
(5.17)  
(5.18)  
(5.19)  
(5.20)

where

\[
\hat{x}_{k|j} = \mathbb{E}_{\lambda_0, \ldots, \lambda_{k-1}, w_0, \ldots, w_{k-1}, v_0, \ldots, v_j} \left[ x_k|y_j \right]
\]

is the conditional expectation of \( x_k \) given \( Y_j^m = \{ y_0^m, y_1^m, \ldots, y_j^m \} \). A-posteriori state estimation error covariance, \( Z_k \), and a-priori state estimation error covariance, \( M_{k+1} \), are defined as follows:

\[
Z_k = \mathbb{E}_{\lambda_0, \ldots, \lambda_{k-1}, w_0, \ldots, w_{k-1}, v_0, \ldots, v_j} \left[ \hat{x}_{k|k} \hat{x}_{k|k}^T \right]
\]

(5.21)

\[
M_{k+1} = \mathbb{E}_{\lambda_0, \ldots, \lambda_k, w_0, \ldots, w_k, v_0, \ldots, v_k} \left[ \hat{x}_{k+1|k} \hat{x}_{k+1|k}^T \right]
\]

where the estimation error is defined by \( \hat{x}_{k|j} = x_k - \hat{x}_{k|j} \). Note that (5.16) to (5.20) are slightly different from the standard Kalman filter equations and the Kalman filter (4.26) to (4.30) used in the last chapter due to the packet loss variables, \( \rho_{k+1} \) and \( \lambda_k \). By combining (5.14) and Kalman filter from (5.16) to (5.20), the optimal control input is calculated as follows:

\[
u_k^* = - [R + B^T P_{k+1} B]^{-1} B^T P_{k+1} A \hat{x}_{k|k}
\]

(5.21)

**Compensation of Packet Loss and Enhancement of Robustness by Disturbance Observer**

The MLQG controller can yield better tracking performance in the networked control than the traditional LQG controller which does not consider packet losses in the system model. Nevertheless it is still a proportional-derivative (PD) controller with more conservative gains than the traditional LQG controller, which is not robust against modeling uncertainties. In this subsection, a DOB is added as an internal loop compensator to cancel the negative effect of packet losses and increase robustness against modeling uncertainties.

The packet loss of the control command from the local host computer to the actuator may be considered as an external disturbance. For example, suppose the control input at
Figure 5.3: A basic block diagram of disturbance observer (DOB) \((y_d: \text{reference}, y: \text{output}, u: \text{control input from controller } C, u_d: \text{control input to cancel disturbance } d, \hat{d}: \text{estimated disturbance}, P_n: \text{nominal model of plant } P, Q: \text{Q filter})\)

Figure 5.4: Overall structure of the proposed controller for a network-based rehabilitation system \((P: \text{actuator in the rehabilitation system}, P_n: \text{nominal model of } P, Q: \text{Q filter in the DOB})\)

If the \(k^{th}\) step is lost, then \(\lambda_k = 0\) and \(u^e_k = 0\) by the zero-input strategy. The zero control input to the actuator may be understood by introducing an external disturbance, i.e.,

\[
\begin{align*}
    u^a_k &= \lambda_k u^e_k = 0 \\
    &= u^e_k + d_k \\
\end{align*}
\]

where \(d_k\) is the introduced external disturbance whose values is \(-u^e_k\) to make the control input to the actuator, \(u^a_k\), zero.

By considering the packet loss as an external disturbance, the DOB can be used to estimate and eliminate the packet loss effect to the system. In general, the DOB is used to [152]:

1) estimate and cancel external disturbance, and
2) compensate for the variation of plant dynamics by treating the variation as an equivalent disturbance.

The basic block diagram of the DOB is shown in Fig. 5.3. To estimate and cancel disturbance, the DOB regards the difference between the actual output and the output of the nominal model as an equivalent disturbance applied to the nominal model. The new control input, \( u_d \), to cancel the disturbance is (time index is omitted here),

\[
 u_d = \frac{1}{1 - Q + \frac{P}{P_n}Q}(u - \frac{P}{P_n} dQ)
\]  
(5.24)

where \( P_n \) is a nominal model of the plant, and \( Q \) is a filter that makes the DOB realizable. Note that if the plant is the same with the nominal model, \( P = P_n \), and \( Q = 1 \), then (5.24) reduces to,

\[
 u_d = u - d
\]  
(5.25)

which is the exact cancellation of the external disturbance. Also, the DOB compensates for the variation of plant dynamics caused by human motions. Therefore, in this application, the DOB is used for two reasons, i.e., the packet loss is estimated and canceled in the same way as the external disturbance is treated by the DOB, and modeling uncertainties in plant dynamics are compensated by considering them as equivalent disturbances.

In the design of the DOB, the selection of the \( Q \) filter is important. The first requirement in the design of the \( Q(s) \) filter is that the order of \( Q(s) \) must be such that \( Q(s)P_n^{-1}(s) \) is realizable. Also, the requirements in (5.26) and (5.27) make the closed-loop system with the DOB robust in terms of performance and stability. Namely, the DOB is effective at frequencies where

\[
 |Q(j\omega)| \approx 1
\]  
(5.26)

The stability condition introduces another constraint, i.e.

\[
 |Q(j\omega)| < |\Delta(j\omega)|^{-1}
\]  
(5.27)

where \( |\Delta(j\omega)| \) is the additive uncertainty of the plant, which is expressed as

\[
 P(s) = P_n(s)[1 + \Delta(s)]
\]  
(5.28)

Notice that (5.26) and (5.27) require the magnitude of the model uncertainty to be less than one over a targeted frequency range. By considering the modeling uncertainty of the actuator [140] and the bandwidth of the human normal walking motion [153], the cut-off frequency of the \( Q \) filter is selected as 10 Hz. For more details about DOB including the design process and the stability condition of the \( Q \) filter, see [154]. In the actual design of the DOB, the identified model of the actuator of cRSEA, \( \frac{1}{4.255 \times 10^{-4}} \), is used as a nominal model[140]. As a result, the dimension of the system is two and the two states are the rotary position and velocity of the DC motor. In the proposed system, the MLQG controller and the DOB were implemented in the local host computer.
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

![Graph showing desired motor trajectory](image)

Figure 5.5: Desired motor trajectory for the simulation study

Overall Controller Structure

The overall controller structure for the proposed network-based rehabilitation system is shown in Fig. 5.4. The host controller in the physical therapist’s side communicates with the local host controller, the gray part in the figure, via the Internet by sending the desired assistive torque command and receiving the patient’s status. The transmitted desired assistive torque, $\tau_{Ad}$, is converted to the desired motor angle, $\theta_{Md}$, by (5.2) (the left “Torque Conversion” block in the figure). The human joint angle, $\theta_H$, is measured by the encoder in cRSEA (“Encoder on the human side” in Fig. 5.1), and wirelessly transmitted to the local host controller. For the simplicity of the block diagram, the human side encoder is not included in the figure, and the line from the human side encoder is simplified as a dashed arrow. Then, the motor is controlled to track the desired angle as accurate as possible by the MLQG controller and the DOB. The state estimator, the Kalman filter, is also not explicitly shown in the figure for simplicity of the block diagram. Two Bernoulli variables for the packet losses are described as switches to select the current signal for successful transmission case or zero for unsuccessful case based on the zero-input strategy. The actuator, $P$, in the rehabilitation device generates the assistive torque, $\tau_A$, and the encoder senses the motor position, $\theta_M$, which is transmitted to the local host controller wirelessly. The generated torque is calculated by (5.1) (the right “Torque Conversion” block in the figure).

5.5.2 Simulation Study

Performance of the proposed controller in Fig. 5.4 is first verified by simulation. As is shown in Fig. 5.2, the Internet communication with an adequately sized packet buffer does not show packet loss, thus the desired torque command is assumed to be received correctly to the local host controller. Packet losses in controller-actuator and sensor-controller channels were simulated by generating two uniformly distributed random variables between 0 and 1, $\alpha_k$ and $\beta_k$. The mechanism of simulating packet loss is as follows:

$$\lambda_k = \begin{cases} 1, & \text{if } \alpha_k \geq \lambda_0 \\ 0, & \text{otherwise} \end{cases}$$ (5.29)
Figure 5.6: Simulation results of different packet loss compensation algorithms

Table 5.1: RMS of tracking errors (deg)

<table>
<thead>
<tr>
<th>Packet loss rate</th>
<th>10%</th>
<th>30%</th>
</tr>
</thead>
<tbody>
<tr>
<td>LQG</td>
<td>0.320</td>
<td>0.507</td>
</tr>
<tr>
<td>MLQG</td>
<td>0.306</td>
<td>0.409</td>
</tr>
<tr>
<td>MLQG + DOB</td>
<td>0.132</td>
<td>0.247</td>
</tr>
</tbody>
</table>

where \( \lambda_0 \) and \( \rho_0 \) are defined in (5.3) and (5.4).

Two different scenarios have been tested in the simulation: the packet loss rate of the local wireless network (both feedback and feedforward channels) was set to 10\% or 30\% by choosing \( \lambda_0 = \rho_0 = 0.9 \) or \( \lambda_0 = \rho_0 = 0.7 \). In this simulation, the human joint is assumed to be stationary, i.e., \( \theta_H = 0 \), and the desired motor angle is given as shown in Fig. 5.5, which is calculated from an arbitrarily given desired assistive torque using (5.2). The weighting matrices in (5.13) were set as

\[
S = Q = \begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = 0.01.
\]
CHAPTER 5. NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

The tracking performance of the proposed controller in Fig. 5.4 is compared with those of two other controllers, the traditional LQG controller which does not include packet loss models the MLQG controller in (5.21) without the DOB. The tracking errors of the three controllers are shown in Fig. 5.6. When the packet loss rate of the local wireless network is set to 10%, the MLQG controller shows slightly better performance than the traditional LQG controller, but the DOB with the MLQG shows significantly better performance than the traditional LQG controller; see Fig. 5.6a. The proposed control algorithm shows much better tracking performance than the two other controllers when the packet loss rate is increased to 30%; see Fig. 5.6b. The RMS tracking errors of the three controllers with different packet loss rates are compared in Table 5.2.

5.5.3 Performance Verification by Experiments

Experimental Setup

The proposed network-based rehabilitation system was realized by two computers communicating with each other via the Internet and the actual knee rehabilitation device (cRSEA). The host controller and the local host controller were programmed by LabVIEW. The data transmission between the two computers via the Internet was actually implemented by LabVIEW. The desired assistive torque command was generated in the host controller as a simple sinusoidal signal, and it was transmitted to the local host controller with transmission rate of 1 kHz. The size of the packet buffer was set to 200.

Packet loss in local wireless network was emulated in the local controller as introduced in the simulations (i.e., generating uniform random numbers) to test performance of the proposed controller with different packet loss rates. Even though the actual wireless hardware was not used in the experiments, performance of the controller can be verified by this experiment as long as packet loss can be represented by Bernoulli random variables. Also, by simulating the packet loss, the tracking performance with different packet loss rates can be compared, and much more severe packet loss situations can be tested.

Experimental Results

The desired motor angle is determined by the human joint and the desired assistive torque. Since the interaction of cRSEA with human motions can increase modeling uncertainties of the plant dynamics, two different experiments, i.e., without and with human motions, were performed to test the robust performance of the proposed controller. The desired joint torque was set to a simple sinusoidal signal with magnitude of 0.5 Nm and frequency of 0.5 Hz as shown in Fig. 5.7a. The experimental results without a knee motion are shown in Fig. 5.7b. The packet loss rate was set to 10%. As is shown in the figure, the desired torque is accurately generated by the controller with small torque errors.

The experimental results with knee motions are shown in Fig. 5.8. The desired assistive torque was the same sinusoidal signal in Fig. 5.8a. The motor was controlled to move
CHAPTER 5. NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

Figure 5.7: Experimental results: no knee motion, 10% packet loss rate

Figure 5.8: Experimental results: arbitrary knee motion, 10% packet loss rate
around the human joint to have appropriate spring deflection as shown in Fig. 5.8a. The torque error in Fig. 5.8b is noisier than Fig. 5.7a due to human motions, but it is still small because of the good tracking performance of the controller. As the packet loss rate increases to 30%, the torque error increases as is shown in Fig. 5.9, but the tracking performance is not significantly degraded. By the simulation and experiments, performance of the proposed method is verified.

5.6 Packet Loss Compensation: A Modified Preview Control Approach

In this section, the preview control technique is modified to incorporate Bernoulli packet loss model into the optimal controller design. Compared to the MLQG control, the preview control considers the tracking error explicitly into the linear quadratic cost function by the reference generator. Additional feedforward control can be then optimally designed to improve the tracking performance in the presence of packet loss. Since this technique requires a reference model, the performance of this algorithm is verified by simulation and experimental results with a DC motor.

5.6.1 Modified Preview Controller Design

In the preview controller design, the system model with packet loss and zero-input strategy (5.9) to (5.12) is considered. In order to achieve improved tracking performance with packet loss, the traditional linear quadratic cost function is modified to include the packet loss model as follows:

\[ J_N = \mathbb{E}_{\lambda_0,\ldots,\lambda_{N-1}} \left[ \sum_{k=0}^{N-1} \left( e_k^T Q e_k + \lambda_k u_k^c R u_k^c \right) + e_N^T Q e_N \right] \]

where \( Q \) and \( R \) are positive semi-definite and positive definite weighting matrices for tracking errors and control inputs, respectively. The tracking error is defined as \( e_k = y_k - r_k \), where
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

$r_k \in \mathbb{R}$ is the reference signal at $k^{th}$ time step. Note that $\lambda_k$ is added to the cost function because of the possible loss of controller packets. Compared to the cost function of the MLQG control (5.13), the tracking error, instead of system state, is incorporated in the cost function. The shaping filter has the form as in (4.9) and reference generator has the same structure as shown in (4.11), and they are omitted in this chapter. Similarly, at the $k^{th}$ time step, current and future reference signals $(r_k, r_{k+1}, \ldots, r_{k+N_p-1}, x_{k+N_p}^r)$ are available for controller design.

To consider the future reference signals for controller design, the plant model and reference model are combined as follows:

$$x_{k+1}^a = A_a x_k^a + B_a u_k^a + B_{wa} w_k$$
$$e_k = C_a x_k^a$$  \hspace{1cm} (5.33)

where

$$x_k^a = [x_k^a] \hspace{1cm} u_k^a = [w_k \ w_{k+N_p-1}] \hspace{1cm} A_a = [A \ 0 \ 0 \ A_d]$$
$$B_a = [B_w \ 0 \ 0 \ B_d] \hspace{1cm} C_a = \begin{bmatrix} C_T^T \ -C_d^T \end{bmatrix}^T$$

Note that $x_k^d$ is the state vector in the reference generator. With the definitions above, the cost function in (5.32) is expressed as follows:

$$J_N = \mathbb{E} \sum_{k=0}^{N-1} (x_k^a S x_k^a + \lambda_k u_k^c S R u_k^c) + x_N^a S x_N^a$$  \hspace{1cm} (5.35)

where $S = C_a^T Q C_a$. The modified preview controller that minimizes the cost function (5.32) is given by the following theorem:

**Theorem 5.1.** Consider the augmented system (5.33), (5.34), and the cost function (5.35). Optimal controller gain at the $k^{th}$ time step is given as

$$L_k = -(R + B_a^T P_{k+1} B_a)^{-1} B_a^T P_{k+1} A_a$$  \hspace{1cm} (5.36)

where $P_k$ is solved backwards recursively using the modified Riccati equation with the initial value $P_N = S = C_a^T Q C_a$ as follows:

$$P_k = A_a^T P_{k+1} A_a + S - \lambda A_a^T P_{k+1} B_a (R + B_a^T P_{k+1} B_a)^{-1} B_a^T P_{k+1} A_a$$  \hspace{1cm} (5.37)

The optimal cost is given by

$$J_{N}^a = b_0 + x_0^a P_0 x_0^a$$  \hspace{1cm} (5.38)

where $P_0$ is given by (5.37) and $b_0$ is calculated backwards recursively by

$$b_k = b_{k+1} + \mathbb{E} \left( w_k^a B_{wa}^T S B_{wa} w_k \right), b_N = 0$$  \hspace{1cm} (5.39)
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

Proof. We first define the minimum cost at the \( k^{th} \) time step as

\[
J_k^o = \min_{U_k^c} \mathbb{E} \left[ \sum_{i=k}^{N-1} \left( x_i^T S x_i + \lambda_i u_i^c R u_i^c + x_N^T S x_N \right) \right]
\]  
(5.40)

where \( U_k^c = \{ u_k^c, \ldots, u_{N-1}^c \} \) and \( k \in \{0, \ldots, N-1\} \). Based on dynamic programming, \( J_k^o \) can be expressed recursively as:

\[
J_k^o = \min_{u_k^c} \mathbb{E} \left( x_k^T S x_k + J_{k+1}^o + \lambda_k u_k^c R u_k^c \right)
\]  
(5.41)

The boundary condition for the recursion is given as:

\[
J_N^o = x_N^T S x_N
\]  
(5.42)

For \( k = N - 1, (5.41) \) can be expressed as

\[
J_{N-1}^o = \min_{u_{N-1}^c} \mathbb{E} \left[ x_{N-1}^T S x_{N-1} + x_N^T S x_N + \lambda_{N-1} u_{N-1}^c R u_{N-1}^c \right]
\]  
(5.43)

It should be noted that \( u_{N-1}^c \) is a combination of two independent zero-mean Gaussian white noises. Moreover, \( x_{N-1}^c \) and \( u_{N-1}^c \) are independent with \( w_{N-1}^a \). Therefore, combining (5.43) with (5.10) and (5.33) gives the following cost function to be minimized:

\[
J_{N-1}^o = \min_{u_{N-1}^c} \mathbb{E} \left[ x_{N-1}^T (S + A_{N-1}^T S A_{N-1}) x_{N-1}^c + u_{N-1}^a T B_{wa}^T S B_{wa} w_{N-1}^a \right] + \lambda_{N-1} u_{N-1}^c T (R + B_{a}^T S B_{a}) u_{N-1}^c + 2 \lambda_{N-1} u_{N-1}^c T B_{a}^T S A_{a} x_{N-1}^a \]  
(5.44)

Now the cost function (5.43) can be minimized by taking the partial derivative of (5.44) with respect to \( u_{N-1}^c \) and setting it to zero. Then, the optimal controller is given as follows:

\[
u_{N-1}^a = - (R + B_{a}^T S B_{a})^{-1} B_{a}^T S A_{a} x_{N-1}^a
\]  
(5.45)

and optimal cost is

\[
J_{N-1}^o = b_{N-1} + x_{N-1}^a T \left[ A_{N-1}^T S A_{N-1} + S - \lambda A_{N-1}^T S B_{a} \left( R + B_{a}^T S B_{a} \right)^{-1} B_{a}^T S A_{a} \right] x_{N-1}^a
\]  
(5.46)

where \( b_{N-1} = \mathbb{E} \left( w_{N-1}^a T B_{wa}^T S B_{wa} w_{N-1}^a \right) \).

Repeating the same process recursively, the optimal controller gain is obtained and given as (5.36), and optimal cost is given by (5.39). Proof is complete.
Similar to the case of MLQG control, modified Kalman filter (5.16) to (5.20) can be applied to estimate the system states \( \hat{x}_{k|k} \). By the modified preview controller gain in (5.36) with the states from Kalman filter and the reference generator, the optimal control input is calculated as follows:

\[
u_k^c = -(R + B_a^T P_{k+1} B_a)^{-1} B_a^T P_{k+1} A_a \hat{x}_{k|k}^a \tag{5.47}
\]

where \( \hat{x}_{k|k}^a = \begin{bmatrix} \hat{x}_{k|k}^r \\ x_k^r \end{bmatrix}^T \). Since \( P_{k+1} \) is calculated backwards recursively, the controller gain is time-varying and inconvenient to be applied in real-time. To overcome this problem, an infinite-horizon steady state optimal controller gain is used in many real applications. In this case, (5.47) becomes

\[
u_k^c = -(R + B_a^T P_{\infty} B_a)^{-1} B_a^T P_{\infty} A_a \hat{x}_{k|k}^a \tag{5.48}
\]

where \( P_{\infty} \) is the steady state solution of (5.37) and can be decomposed into the following form [155]:

\[
P_{\infty} = \begin{bmatrix} P_{1\infty}^1 & P_{1\infty}^3 \\ P_{3\infty}^T & P_{2\infty}^\infty \end{bmatrix}
\]

Then, the optimal controller (5.48) can be reformulated as

\[
u_k^c = -(R + B^T P_{\infty}^1 B)^{-1} B^T (P_{1\infty}^1 A_a \hat{x}_{k|k} + P_{3\infty}^3 A_d x_k^d) \tag{5.49}
\]

where \( P_{1\infty}^1 \) and \( P_{3\infty}^3 \) can be calculated by solving the algebraic Riccati equation as follows:

\[
P_{1\infty}^1 = C^T Q C + A^T P_{1\infty}^1 A - \lambda A^T P_{1\infty}^1 B (B^T P_{1\infty}^1 B + R)^{-1} B^T P_{1\infty}^1 A \tag{5.50}
\]

\[
P_{3\infty}^3 = -C^T Q C_d + A^T P_{3\infty}^3 A_d - \lambda A^T P_{3\infty}^3 B (B^T P_{3\infty}^3 B + R)^{-1} B^T P_{3\infty}^3 A_d \tag{5.51}
\]
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

![Reference Signals](image)

Figure 5.11: Reference signals from reference generator

Note that the controller signal in (5.49) consists of state feedback control and reference feedforward control. The enhanced tracking performance of the preview control can be explained by the additional reference feedforward controller signal. Figure 5.10 shows the block diagram of the proposed modified preview control system.

The proposed control algorithm in (5.49) is similar to the conventional preview controller in the sense of combining the plant states and the reference generator states [128]. The difference lies in the consideration of the packet loss model in designing the preview controller.

Remark 5.1. As is shown in (5.49), the optimal controller combines feedback and feedforward control, and it is well known that feedforward control does not affect the stability of the closed-loop system. Therefore, we just need to consider whether the feedback controller can stabilize the system. Moreover, (5.50) is the same modified Riccati equation for designing MLQG controller in [141], which allows us to use the stability analysis results in previous MLQG control studies. If there is no packet loss in the system, it is known that a standard LQG controller can always be found to stabilize the original system. However, when packet loss happens, the system cannot be stabilized if $\lambda$ and $\rho$ are below some critical values $\lambda^*$ and $\rho^*$, which can be calculated by solving a set of LMIs, as is shown in Theorem 2 in [156].

5.6.2 Simulation Study

Simulation Setup and Choice of Preview Horizon

Performance of the proposed modified preview controller is first verified by some simulation studies. The mechanism of simulating packet loss was the same as (5.29) and (5.30).

An open-loop stable brushless DC (BLDC) motor was chosen as the plant, so applying Remark 5.1 gave $\lambda^* = 0$ and $\rho^* = 0$. In other words, we may find stabilizing controllers for any packet loss rates. In the simulation study, two different scenarios of packet loss were investigated: 10% and 20% packet loss in both feedback and feedforward channels were simulated by choosing $\lambda = \rho = 0.9$ and $\lambda = \rho = 0.8$, respectively.

In the simulations, the sampling rate was set to 1 kHz for precise motion control. In the modified preview controller design, weighting matrices $Q$ and $R$ in (5.32) were chosen to be
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

1 and 7, which were tuned manually based on the simulation and experimental results. The desired trajectory was generated by the the same reference generator as (4.33) in the last chapter. The reference trajectory of the motor is shown in Fig. 5.11.

It has been confirmed in Section 5.5 that introducing Bernoulli packet loss model into LQG controller design could improve the tracking performance compared to conventional LQG control. Therefore, in this section, emphasis is given to the effectiveness of feedforward controller.

It is very important to decide a reasonable preview horizon for feedforward controller design. It was discussed in Section 4.3.3 that a good estimate of the maximum effective preview horizon $N_{pc}$ can be three times the longest closed-loop plant time constant, which can be approximated by the settling time with 5% tolerance. We can approximate $N_{pc}$ using the following procedures:

**Step 1**: calculate the eigenvalues of the closed loop system with the optimal feedback control gain.

**Step 2**: pick up the eigenvalue corresponding to the longest closed-loop plant time constant. This can be achieved by comparing the distance between the eigenvalues and unit circle in the complex plane. The resulting eigenvalue is expressed as $z_0$.

**Step 3**: based on the definition of settling time, the maximum effective preview horizon $N_{pc}$ can be reached by solving the following equation:

$$|z_0|^{N_{pc}} = 0.05$$  \hspace{1cm} (5.52)
Based on the algorithm above and the system model, we got that $N_{pc} = 74.9139 \approx 75$ for 10% packet loss and $N_{pc} = 69.8184 \approx 70$ for 20% packet loss. This can be explained as follows: when packet loss is more serious, the tracking performance will be saturated more easily in terms of the preview horizon with our settings of $Q$ and $R$ in the cost function. To compare the tracking performance with different preview horizons, $N_p$ was chosen to be 0, 10, 20, 30, 40, 50, 60, 65, 70, 75, 80, and 200 for each packet loss scenario.

**Simulation Results and Discussions**

Performance of the proposed controller is highly dependent on accuracy of the estimated states by the modified Kalman filter from (5.16) to (5.20). In order to verify the performance of the modified Kalman filter, the estimated position and velocity with a packet loss rate of 20% is compared with actual position and velocity output. As is shown in Fig. 5.12a, the estimated value of position is very accurate even with noise and high packet loss rate. Figure 5.12b demonstrates that the estimated velocity is smoother than the actual velocity calculated by direct differentiation of position measurement.

Tracking performance of the proposed controller with $N_p = 65$, 70, and 75 is compared in Fig. 5.13. For both packet loss rates, three preview horizons result in very similar tracking errors. In order to further compare the performance, the RMS tracking errors and values of
Table 5.2: RMS tracking errors in simulations with an open-loop stable plant (deg)

<table>
<thead>
<tr>
<th>Preview Horizon</th>
<th>10% Packet Loss</th>
<th>20% Packet Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p = 0$</td>
<td>0.4522</td>
<td>0.4718</td>
</tr>
<tr>
<td>$N_p = 10$</td>
<td>0.1710</td>
<td>0.1828</td>
</tr>
<tr>
<td>$N_p = 20$</td>
<td>0.1285</td>
<td>0.1383</td>
</tr>
<tr>
<td>$N_p = 30$</td>
<td>0.1693</td>
<td>0.1746</td>
</tr>
<tr>
<td>$N_p = 40$</td>
<td>0.1891</td>
<td>0.1969</td>
</tr>
<tr>
<td>$N_p = 50$</td>
<td>0.1926</td>
<td>0.2027</td>
</tr>
<tr>
<td>$N_p = 60$</td>
<td>0.1903</td>
<td>0.2001</td>
</tr>
<tr>
<td>$N_p = 70$</td>
<td>0.1889</td>
<td>0.1995</td>
</tr>
<tr>
<td>$N_p = 80$</td>
<td>0.1893</td>
<td>0.2018</td>
</tr>
<tr>
<td>$N_p = 200$</td>
<td>0.1961</td>
<td>0.2036</td>
</tr>
</tbody>
</table>

Table 5.3: Values of cost function in simulations with an open-loop stable plant

<table>
<thead>
<tr>
<th>Preview Horizon</th>
<th>10% Packet Loss</th>
<th>20% Packet Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p = 0$</td>
<td>2991.8</td>
<td>3208.6</td>
</tr>
<tr>
<td>$N_p = 10$</td>
<td>1661.6</td>
<td>1836.5</td>
</tr>
<tr>
<td>$N_p = 20$</td>
<td>1143.3</td>
<td>1298.0</td>
</tr>
<tr>
<td>$N_p = 30$</td>
<td>982.7</td>
<td>1084.1</td>
</tr>
<tr>
<td>$N_p = 40$</td>
<td>931.9</td>
<td>1043.3</td>
</tr>
<tr>
<td>$N_p = 50$</td>
<td>943.4</td>
<td>1048.7</td>
</tr>
<tr>
<td>$N_p = 60$</td>
<td>947.7</td>
<td>1045.5</td>
</tr>
<tr>
<td>$N_p = 70$</td>
<td>936.9</td>
<td>1045.6</td>
</tr>
<tr>
<td>$N_p = 80$</td>
<td>930.0</td>
<td>1040.4</td>
</tr>
<tr>
<td>$N_p = 200$</td>
<td>928.9</td>
<td>1025.0</td>
</tr>
</tbody>
</table>
Figure 5.14: Simulation results with different preview horizons and an open-loop stable plant

the cost function (5.32) with different preview horizons and packet loss rates are compared in Table 5.2, Table 5.3, and Fig. 5.14.

Based on the results in Table 5.2 and Fig. 5.14a, \( N_p = 0 \) gives the largest tracking errors because the modified preview controller degenerates to a MLQG regulator in this case, as is shown in [141]. The RMS tracking errors drop down dramatically when some feedforward control is added, as is shown in the case with \( N_p = 10 \) and 20. Further increasing the preview horizon (\( N_p = 30, 40, \) and 50) does not necessarily further reduce the tracking error because reducing control input will contribute more to the minimization of the cost function (5.32) given our choice of weighting functions. When \( N_p \) increases to around \( N_{pc} \) (\( N_p = 60, 70, \) and 80), satisfactory tracking performance is achieved and tracking error converges to a steady value. \( N_p = 200 \) does not necessarily yield the smallest RMS tracking errors. The RMS tracking error increases when the packet loss rate increases for each choice of preview horizon including the case when \( N_p = 0 \).

From Table 5.3 and Fig. 5.14b, \( N_p = 0 \) yields the largest cost because there is no preview in the controller design. As the preview horizon increases to around \( N_{pc} \), the cost decreases dramatically and converges to a steady value. Further increasing \( N_p \) to 200 leads to similar values of cost compared to the case with \( N_p \approx N_{pc} \) (see Table 5.3). As packet loss rate increases from 10% to 20%, cost increases for each preview horizon.

Simulation results above suggest that the preview horizon does not need to reach the \( N_{pc} \) proposed by (5.52) to achieve satisfactory tracking performance. It could be seen that the
Figure 5.15: Simulation results of modified preview controllers with an open-loop unstable plant

RMS tracking errors and values of cost function converge to a small value even when \( N_p \) is smaller than \( N_{pc} \). Nevertheless, (5.52) could be used as a guideline of choosing preview horizon to facilitate controller design.

Based on the simulation results, the following remarks can be reached:

**Remark 5.2.** When \( N_p = 0 \), the since there is no preview information available for the controller design, the modified preview controller degrades to a MLQG controller. Larger tracking error and cost can be expected compared to the cases when previewed reference is available.

**Remark 5.3.** When short preview is available (\( N_p = 10 \) and 20), tracking errors and cost decrease dramatically. Actually satisfactory tracking performance and small cost can be achieved in this case. Therefore, the modified preview controller can be applied even if small preview with \( N_p < N_{pc} \) is available. Further increasing the preview horizon does not necessarily increase the tracking performance (\( N_p = 30, 40, \) and 50), but it definitely reduce the cost compared to case with short preview.

**Remark 5.4.** It should be noted that choosing \( N_p = N_{pc} \) doesn’t necessarily yield the optimal system performance (\( N_p = 60, 65, 70, 75, \) and 80), but \( N_{pc} \) provides a guideline about how
Table 5.4: RMS tracking errors in simulations with an open-loop unstable plant (deg)

<table>
<thead>
<tr>
<th>Preview Horizon</th>
<th>10% Packet Loss</th>
<th>20% Packet Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p = 0$</td>
<td>0.4719</td>
<td>0.4931</td>
</tr>
<tr>
<td>$N_p = 10$</td>
<td>0.1739</td>
<td>0.1923</td>
</tr>
<tr>
<td>$N_p = 20$</td>
<td>0.1294</td>
<td>0.1382</td>
</tr>
<tr>
<td>$N_p = 30$</td>
<td>0.1686</td>
<td>0.1743</td>
</tr>
<tr>
<td>$N_p = 40$</td>
<td>0.1902</td>
<td>0.1943</td>
</tr>
<tr>
<td>$N_p = 50$</td>
<td>0.1944</td>
<td>0.2036</td>
</tr>
<tr>
<td>$N_p = 60$</td>
<td>0.1898</td>
<td>0.2056</td>
</tr>
<tr>
<td>$N_p = 70$</td>
<td>0.1883</td>
<td>0.1993</td>
</tr>
<tr>
<td>$N_p = 80$</td>
<td>0.1920</td>
<td>0.2022</td>
</tr>
<tr>
<td>$N_p = 200$</td>
<td>0.1970</td>
<td>0.2091</td>
</tr>
</tbody>
</table>

Table 5.5: Values of cost function in simulations with an open-loop unstable plant

<table>
<thead>
<tr>
<th>Preview Horizon</th>
<th>10% Packet Loss</th>
<th>20% Packet Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p = 0$</td>
<td>4200.9</td>
<td>4622.1</td>
</tr>
<tr>
<td>$N_p = 10$</td>
<td>1664.5</td>
<td>1870.6</td>
</tr>
<tr>
<td>$N_p = 20$</td>
<td>1153.8</td>
<td>1309.2</td>
</tr>
<tr>
<td>$N_p = 30$</td>
<td>991.2</td>
<td>1103.2</td>
</tr>
<tr>
<td>$N_p = 40$</td>
<td>946.6</td>
<td>1078.3</td>
</tr>
<tr>
<td>$N_p = 50$</td>
<td>943.9</td>
<td>1074.0</td>
</tr>
<tr>
<td>$N_p = 60$</td>
<td>954.3</td>
<td>1053.3</td>
</tr>
<tr>
<td>$N_p = 70$</td>
<td>947.4</td>
<td>1056.8</td>
</tr>
<tr>
<td>$N_p = 80$</td>
<td>944.0</td>
<td>1044.2</td>
</tr>
<tr>
<td>$N_p = 200$</td>
<td>928.8</td>
<td>1033.2</td>
</tr>
</tbody>
</table>
large the $N_p$ should be to guarantee satisfactory tracking performance. Based on the simulation results, it can be inferred that $N_{pc}$ provides a conservative choice of preview horizon, and even much shorter preview might yield very good tracking performance.

**Remark 5.5.** When $N_p \gg N_{pc}$ ($N_p = 200$), the tracking performance may be further enhanced and the cost may further decrease, but only very limited improvement can be achieved compared to the case when $N_p \approx N_{pc}$. This is because the performance improvement brought by the feedforward control will saturate in this case. Moreover, too large $N_p$ may not be feasible in many applications because reference signals for a far future may not be available. It will also add heavy computation load to the controller. As a result, large preview horizons should be carefully employed in controller design.

**Simulation with an Unstable Plant**

To further demonstrate the performance of the proposed controller, some simulations were conducted with an open-loop unstable plant. The continuous second-order plant was chosen to have one pole at the origin and the other one at 13.92, which was clearly an unstable pole. Based on Remark 5.1, we got $\lambda^* = \rho^* = 0.027$. The same cost function and parameters were used for the set of simulations with this unstable plant. The proposed procedures in the subsection above yielded $N_{pc} = 71.9356 \approx 72$ for 10% packet loss and $N_{pc} = 64.2497 \approx 65$
CHAPTER 5  NETWORKED CONTROL OF AN ASSISTIVE ROBOT: PACKET LOSS COMPENSATION

for 20% packet loss. The same reference trajectory was used as in Section 5.6.2. The same preview horizons were chosen as in the cases with an open-loop stable plant.

Tracking errors of the proposed control system with the unstable plant are shown in Fig. 5.15. It can be seen that the closed-loop system is stable and similar tracking performance is achieved compared to the control system with the stable plant. RMS tracking errors and values of the cost function are shown in Table 5.4, Table 5.5, and Fig. 5.16, from which the proposed controller is verified to achieve very good tracking performance even with an unstable plant. Similar conclusion can be drawn regarding the choice of the preview horizon. It can also be seen that the cost with $N_p = 0$ is much larger for the unstable plant due to the larger control input to stabilize the system. However, when some preview information is available, the cost for controlling the open-loop unstable plant is similar to the case of controlling the open-loop stable plant. This can be considered as the additional benefit of incorporating future reference signals into the controller design.

5.6.3 Experimental Study

Experimental Setup

In this section, performance of the proposed control algorithm is verified by experiments. The experiment setup was shown in Fig. 5.17. The BLDC motor was connected to a local computer and controlled by LabVIEW in real time. Packet loss in the wireless network was emulated in the local computer as introduced in the simulations (i.e., sampling from uniform distribution) to test the performance of the proposed controllers with different packet loss rates. The sampling rate was also set to 1 kHz, and the same reference shown in Fig. 4.9 was used in the experiments as the desired trajectory. Even though the actual wireless hardware was not used in the experiments, performance of the proposed controller can still be verified by the experiments as long as packet loss can be represented by Bernoulli random variables. Also, by simulating the packet loss, tracking performance with different packet loss rates can be compared, and performance of the proposed controller under much more severe packet loss scenarios can be tested. In the two sets of experiments, packet loss rates in both controller-actuator and sensor-controller channels were set to 10% and 20%, respectively. The same
weighting matrices were used as in simulations. Based on the discussion in the simulation part, preview horizon was set to be 0, 10, 20, 60, 65, 70, 75, 80, and 200 in experiments.

### Experimental Results

Tracking performance of the modified preview controller with preview horizon 65, 70, and 75 is compared in Fig. 5.18. It can be observed that the three choices of preview horizon give very small tracking errors for both the packet loss rates of 10% and 20%, which is

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Table 5.6: RMS tracking errors in experiments (deg)

<table>
<thead>
<tr>
<th>Preview Horizon</th>
<th>10% Packet Loss</th>
<th>20% Packet Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p = 0$</td>
<td>0.8043</td>
<td>0.8162</td>
</tr>
<tr>
<td>$N_p = 10$</td>
<td>0.3302</td>
<td>0.3495</td>
</tr>
<tr>
<td>$N_p = 20$</td>
<td>0.3003</td>
<td>0.3121</td>
</tr>
<tr>
<td>$N_p = 60$</td>
<td>0.3690</td>
<td>0.3919</td>
</tr>
<tr>
<td>$N_p = 70$</td>
<td>0.3651</td>
<td>0.3904</td>
</tr>
<tr>
<td>$N_p = 80$</td>
<td>0.3645</td>
<td>0.3825</td>
</tr>
<tr>
<td>$N_p = 200$</td>
<td>0.3403</td>
<td>0.3439</td>
</tr>
</tbody>
</table>
similar to analytical and simulation results. In order to further compare the performance, the RMS tracking errors and cost functions with different packet loss rates are also compared in Tables 5.6 and 5.7.

As is shown in the tables, \( N_p = 200 \) yields the smallest values of cost functions. For both packet loss scenarios, when \( N_p \) increases to values around 70, tracking errors become steady and small, which is consistent with analytical and simulation results. 20% packet loss yields larger tracking error than 10% packet loss for each choice of preview horizon including \( N_p = 0 \). Compared to the simulation results, larger tracking errors and cost values are observed for each case but conclusions about the choice of preview horizon are successfully verified.

## 5.7 Chapter Summary

In this chapter, another challenge in a NCS, packet loss, was investigated and two different approaches were proposed. The robotic assistive device, cRSEA, was briefly introduced and Bernoulli random process was employed to model the random packet loss. A MLQG controller was enhanced with a DOB to achieve good tracking performance under packet loss and strong disturbance from human-robot interactions. Simulation and experimental results verified the superior performance compared to LQG and MLQG techniques. As a second approach, the preview control technique was employed to achieve satisfactory tracking performance by introducing feedforward control into the system. The choice of preview horizon was examined and performance was verified by simulations and experiments.
Chapter 6

Conclusions and Open Problems

6.1 Concluding Remarks

This dissertation investigated several fundamental problems in the design a networked rehabilitation system, and the design methodologies could be extended into a broad range of CPSs. The work presented in this dissertation could be summarized as (1) structure design of the networked rehabilitation system; (2) design of a wireless human motion monitoring system and clinical evaluations; (3) NCS design to handle time delay; (4) NCS design to handle packet loss. Figure 6.1 illustrates how the proposed general CPS design structure applies to this problem.

![Diagram](image)

Figure 6.1: Layered design of the networked rehabilitation system using a cyber-physical system approach
Structure Design of the Networked Rehabilitation System

Structure of the networked rehabilitation system was proposed in Chapter 1 to coordinate all the work presented in this dissertation. The system was geographically divided into patient side and therapist side. On the patient side, sensors and robotic devices were worn by the patients with visual feedback. Patients' data were transmitted through Internet to the therapist in a remote side. The networked rehabilitation system enabled in-home rehabilitation so that it was more convenient and private for patients to conduct gait exercise. Moreover, since sensors and robotic devices were introduced, most of the work could be completed by the system automatically. As a result, one therapist could work with multiple patients simultaneously by monitoring patients' activities remotely and providing feedback if necessary.

Design of Wireless Human Motion Monitoring System

As the first step to achieve networked rehabilitation, several wireless sensors, including smart shoes and IMU sensors, were introduced into the system to analyze the user's gait in Chapter 2. Several metrics, such as gait phases, step length, and center of pressure (CoP), could be calculated based on the raw data from the sensors. User interfaces were developed on a laptop and an iPad. Experimental results clearly showed different gait characters between healthy subjects and patients. A clinical study was designed to evaluate the effectiveness of introducing visual feedback into rehabilitation training, as presented in Chapter 3. Patients were randomly assigned into control and experimental groups. Patients in the control group received supervised gait training with therapists, and those in the experimental group conducted gait exercise based on visual feedback. Gait improvement was evaluated using both standardized clinical tools as well as gait parameters from sensory data. It was confirmed that similar gait improvement was made for patients in two groups, which indicated patients could rely on visual feedback to direct their gait exercise at home.

Networked Control System Design

A significant amount of effort was put into the networked control system (NCS) design for the robotic assistive device. A real-time and high-speed wireless communication protocol called RT-WiFi was designed in Chapter 4. A preview control technique and a double disturbance observer (DDOB) approach were investigated to compensate for the negative effect of time delay. Another challenge, packet loss, was discussed and handled in Chapter 5. A modified preview controller was proposed to find the optimal controller for packet loss compensation. A MLQG controller was combined with a disturbance observer to handle both packet loss as well as the external disturbance and modeling uncertainties. All the proposed algorithms were verified by simulation and experimental results.
6.2 Open Problems

Although this dissertation discussed many problems in the design of a NGRS, there are still many open problems that need to be further addressed and they will be investigated as future work.

**Mechatronic Design of Assistive Robot and User Interface**

In this dissertation, the compact rotary elastic actuator (cRSEA) was used for validation of the networked control algorithms. The assistive device needs to be light, energy-efficient, and able to provide enough assistance. Moreover, the cRSEA can only apply to assistive torque to the user’s knee joint, and the new device should employ multiple actuators to provide assistance to both hip and knee joints. This also leads to the control problem of multi-actuator coordination. Furthermore, the assistive robot needs to be equipped with wireless communication interface so as to be coordinated and controlled remotely.

Besides the design of assistive robot, the user interfaces also need to be improved so that more intuitive visual feedback can be provided to the users. For example, the visual feedback should provide users more clear messages about how they should change their gait behaviors, instead of just demonstrating the gait information. In addition, other types of biofeedback, such as verbal and haptic feedback, can be introduced to the user interfaces to more efficiently guide the gait exercise.

**Trajectory Planning of the Assistive Robot**

In this dissertation, more emphasis was put in the networked motion control of the assistive robot given the desired trajectory. The desired assistive torque was assumed to be developed already. However, it might be difficult to design the desired assistive torque in real clinical environment. The trajectory planning of the assistive robot requires a deep understanding of the patient’s gait abnormality as well as biomechanics to determine the appropriate assistive torque. Machine learning approaches might be applied to build the relationship between the patients gait behaviors to the desired assistive torque, and training data can be obtained by measuring gait information and the amount of assistive torque given by the physical therapist.

**Large-scale Rehabilitation based on Cloud Computing**

As there are more and more patients requiring physical therapy, the central high-level decision making unit has to serve more patients in the local side simultaneously. This not only adds a lot of load in the communication channel, but also requires a large amount of computation power in the central server for gait analysis and trajectory planning. Moreover, trajectory planning algorithm usually requires a large amount of measurement data from other patients for reference. Introducing cloud computing techniques into this system might help tackle this challenge, and high-level computers can be remotely located to jointly serve patients.
It should be noted that the decision making and trajectory planning algorithms need to be parallelized before it can be implemented in the cloud computing platform.

**Safety Enhancement of the Networked Rehabilitation System**

Since the proposed system works with patients directly, its safety needs to be carefully studied, especially for the actuation part. In our work [135], a human motion model was studied, and one important application is to achieve joint motion prediction so that some intervention can be enabled if the patient joint motion is anticipated to enter the predefined danger zone. The actuators also need to be designed with adequate safety mechanisms [157]. Besides safety, it is also important to guarantee the security of data transmission in the system, as the patients’ information should be kept strictly confidential.

**Validation of the Networked Rehabilitation System with Patients**

In this dissertation, part of the system was verified with a small group of patients to confirm its effectiveness. The actuation system needs to be clinically examined with patients in the future. The major challenge is how to recruit large enough number of representative patients to clinically verify the effectiveness of the overall system. The first step of the clinical verification needs to be conducted at the rehabilitation clinic with the supervision of physical therapists. Once the performance of the system is verified, patients can start to conduct gait exercise at home with remote health monitoring by the therapist to make sure the system performance is similar to the case when patient is on site.

**Extension of the Design Philosophy to Other Cyber-Physical Systems**

This dissertation aimed at developing general design philosophy for the design of cyber-physical systems, and the networked rehabilitation system is just one (very good) example. The layered design structure and all mechatronic techniques applied in this design can certainly be extended to other cyber-physical systems, such as autonomous vehicles, transportation systems, energy systems, and human-robot interactions. While all the systems share the same design structure, they have different characteristics and requirements, which makes the design of CPSs a challenging but interesting and promising research topic.
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