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To the Graduate Council:

I am submitting herewith a thesis written by Fengpei Yuan entitled "Development of a Dynamical Systems Model and Adaptive Intervention Strategy for Stroke Rehabilitation." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Mechanical Engineering.

Eric R. Wade, Major Professor

We have read this thesis and recommend its acceptance:

Jeffrey A. Reinbolt, Xiaopeng Zhao

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Vice Provost and Dean of the Graduate School

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Development of a Dynamical Systems Model and Adaptive Intervention Strategy for Stroke Rehabilitation

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Fengpei Yuan

May 2019

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I dedicate this thesis to my family, who have been always loving and supporting me in my life.

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Acknowledgments

This thesis is a summary of my two-year research life, full of pain and joy. I would like to thank all the people who have helped me and encouraged me to go through this wonderful experience.

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Abstract

Each year, approximately 795000 people experience stroke in the United States. After stroke onset, about 80% of patients suffer from hemiparesis, the weakness of face or limb on one side. These people outside clinical setting may develop learned nonuse, which may result in long-term limitation in the outcome of motor recovery. Interventions such as the Constraint Induced Movement Therapy has shown promise in reversing nonuse. However, many chronic individuals do not have access to such training programs. Therefore, some novel tools capable of continuous monitoring patients' health status and furthermore providing appropriate interventions for patients in ambient setting is required to optimize stroke rehabilitation.

Dynamical systems modeling combined with wearable technologies may allow to quantitatively describe nonuse evolution. We developed and validated a pendulum-based dynamical model using experimental and simulated motion data. Without direct access to internal torques, we proposed an inverse dynamics-based metric to quantify and compare motor performance between limbs. The primary outcome measure is RMSE between the simulated driving torque for experimental and reference motions. Using RMSEs, we defined a novel within-person comparison factor $w_{limb}^{participant}$ $[w]$, and compared it to the Fugl-Mayer Assessment score. Our dynamic model is capable of mimicking upper-extremity shoulder flexion dynamics. RMSE is sensitive to differences in motor performance between limbs for both groups. Finally, the factor $w_{limb}^{participant}$ $[w]$ is related to post-stroke severity. The arm dynamical model may have great potential for monitoring time-varying motor impairment using noninvasive sensing.

Markov decision process (MDP) is a comparatively simple approach of simulation modelling. We implemented MDP to understand the primary factors behind human dynamic decision making on limb choice during rehabilitation. The model showed good performance in

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understanding the crucial motivators (or barriers) underlying patients' behaviors. We found that a patient with higher motivation, greater perceived benefits of paretic-limb use, and milder motor impairment, would show a better adherence to using paretic limb in physical activity, which suggests that we may provide related interventions in clinical practice to promote a better recovery outcome. MDP modelling may be suggestive in designing cost-effective adaptive intervention for stroke rehabilitation.

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Table of Contents

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المنارة للاستشارات
www.manaraa.com

www.manaraa.com

List of Tables

www.manaraa.com

List of Figures

المنارة للاستشارات

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Chapter 1

Introduction

Each year, there are approximately $795,000$ people attacked by stroke in the United States. Now stroke has become the fifth leading killer and also the leading cause of serious long-term disabilities. Stroke patients may suffer physically from motor disability and functional disability, and psychologically from depression and anxiety. Now the increasing number of stroke patients has impose considerable burden to patients, family and society. After stroke onset, about 80% of patients suffer from hemiparesis, the weakness of face, arm or leg on one side. More worsely, these people outside of clinical setting may develop learned nonuse, which may result in long-term suppression of use of the paretic limb and consequently limitation in the outcome of motor recovery.

Fortunately, interventions such as the Constraint Induced Movement Therapy has shown promise in reversing nonuse. However, on one hand, patients in such training programs cannot adhere to exercise as prescribed; on the other hand, many chronic individuals do not have access to such training programs. Therefore, some novel tools capable of continuous monitoring patients' health status and furthermore providing appropriate interventions for patients outside of the clinical setting is required for an optimal outcome of stroke rehabilitation.

Dynamical systems modeling combined with wearable technologies may allow for quantitative descriptions of nonuse evolution. Our first goal is to develop a novel, simplified physical model to mimic upper-extremity dynamics during shoulder flexion for post-stroke individuals. We developed and validated a pendulum-based dynamical model

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using experimental and simulated motion data. Without direct access to internal torques, we proposed an inverse dynamics-based metric to quantify and compare motor performance between limbs. The primary outcome measure is RMSE between the simulated driving torque for experimental and reference motions. Using RMSEs, we defined a novel within-person comparison factor, $w_{limb}^{participant}$, and compared it to the Fugl-Mayer Assessment score. For controls, derived RMSEs between the dominant and non-dominant arms were similar. Post-stroke participants showed greater difference in between-limb RMSE magnitude. There was a statistically significant difference ($U = 5$, $p = 0.041$) between $w_{nondominant}^{control}$ for controls and $w_{paretic}^{stroke}$ for post-stroke. Our dynamic model is capable of mimicking upper-extremity shoulder flexion dynamics. RMSE is sensitive to differences in motor performance between limbs for both groups. Finally, $w_{limb}^{participant}$ is related to post-stroke severity. The arm dynamical model may have great potential for monitoring time-varying motor impairment using noninvasive sensing.

Markov decision process (MDP) is a comparatively simple approach of simulation modelling. Our second goal is to apply the method of MDP to understand the primary controlling factors (motivator or barrier) behind human dynamic decision making on limb choice during rehabilitation process. We implemented the MDP model for our specific context, where post-stroke patients perform tasks with their paretic or non-paretic limb during their physical activities. There are three states defined according to patients' motivation level, and two actions (paretic- and nonparetic- limb use) in our MDP model. The immediate reward function R is constructed considering patients' physiological and psychological ability. Moreover, we proposed a measurement, e_d [dangerous epoch], to represent the optimal decisions derived by our MDP. The model showed good performance in understanding the crucial motivators (or barriers) underlying patients' behavior of suppression of paretic-limb use. We found that a patient with higher motivation, greater perceived benefits of paretic-limb use, milder motor impairment and a larger discount factor, would show a better adherence to using paretic limb in physical activity, which suggests that we may provide related interventions in clinical practice to improve modulate these variables and thus promote a better recovery outcome. The Markov decision process model may be suggestive in the design of cost-effective adaptive intervention for stroke rehabilitation.

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Chapter 2

Background

2.1 Introduction to Stroke and Sequelae

Each year, approximately 795,000 people experience a new or recurrent stroke in the United States. On average, every 40 seconds someone, who can be children, young or older adults, is attacked by stroke. From 2006 to 2016 the number of stroke death increased 3.7 % and in 2016 about one out of every 19 deaths in the United States was caused by stroke. Now stroke has become the fifth leading killer and also the leading cause of serious long-term disabilities. In order to provide more available, efficient and convenient care for patients with stroke, a family of services have been developed, e.g., organizations of stroke center, hospitals inpatient stays, outpatient visits, prescribed medicines, and home health care [1, 2]. It was estimated that in 2015 the total direct medical cost for stroke care was $27.6 billion [3] and the mean expenditure per patient was $8218 in the United States [4]. Now both the increasing number of stroke patients and the expensive expenditure impose considerable challenge and burden to patients, families and society.

From the perspective of causes, there are two types of stroke, ischemic stroke and hemorrhagic stroke. The former one, 87 % of all strokes, is caused by a blood clot blocking or plugging a blood vessel in the brain. The latter one is caused by the blood vessel that breaks and bleeds into the brain. Additionally, from the perspective of biology of recovery, post-stroke patients will experience acute phase, sub-acute phase, and chronic phase, although that there is slight difference in the concrete definitions of these three timepoints. While

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the acute phase is consistently defined as the time within a week of stroke onset, there is no consensus on the definitions of sub-acute and chronic phase. For example, the chronic phase was defined as the time beyond three weeks from the stroke onset in [5] but beyond six months in [6]. No matter which stage patients are experiencing, they may suffer physically from weakness of face, arm or leg, posture instability, loss of balance or coordination, decreased range of motion, and cognitive impairment, and psychologically from depression and anxiety, both of which lead to a decline in the quality of life for these patients over periods [7–9].

Meanwhile, the weakness of face, arm or leg, is especially on one side (the paretic side) of human body, also called *hemiparesis*, which is one of the most common, disabling sequelae of stroke and affects about 80% of patients. Individuals with hemiparesis not only have greater difficulty in performing activities of daily living (ADLs) in the recovery process, but also may develop poor motor function and abnormal movement pattern in a long term perspective [10]. Although the initial severity of hemiparesis (assessed within a week after stroke onset) is found to be the most significant predictor of motor recovery and functional outcomes, that is , generally a more severe initial motor impairment is associated with a comparatively worse motor recovery [11, 12], however, stroke survivors with the same initial severity (severe, moderate or mild) of paresis may exhibit different extent of motor recovery (complete or partial recovery) in future. For example, in the 6-month follow-up period by Bonita and Beaglehole [13], 22% of individuals with moderate paresis on admission showed complete recovery while 31% showed partial recovery. The eventual motor recovery in stroke survivors is the combined results of personal factors and environmental factors.

During the rehabilitation of hemiparesis, one of the well-known phenomenon is the *learned non-use*, that individuals tend to suppress or to not use the paretic limb even though they posses the sufficient motor ability in their paretic limb to complete a task [14]. For example, Andrews and Stewart [15] found that there was a difference in what patients with stroke could do in the hospital and did do at home. This learned non-use phenomenon often evolves or is reinforced in the sub-acute and chronic stages of stroke recovery. The decision of learned non-use may lead to an immediate benefits (e.g., less pain, less effort, and more successful movements), but in the long-term, may be detrimental to the outcome and may limit the recovery of normal motor patterns [16–18]. As a result, it was suggested that more

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post-stroke recovery would have occurred had phenomenon of learned non-use restrained and/or counteracted [10]. In other words, the more patients with hemiparesis use and/or practice their paretic limb, the more true motor recovery they will approach to, which is fundamental to many proposed rehabilitation therapies in development, for example, the constraint-induced movement therapy (CIMT, training the paretic arm use with the restraint of the ipsilesional limb) [19, 20], and the robot-assisted therapy, both of which significantly improved the motor function for patients with stroke in a long term, compared the usual care [21, 22].

2.2 Post-Stroke Rehabilitation

Generally, from the onset of stroke, patients stay in the hospital for about one week to treat the acute stroke. Acute therapies are provided to try to stop the stroke by quickly dissolving the blood or by stopping bleeding. After the vital neurological symptoms are stable, stroke survivors with impairments discharge from the hospital. In terms of the discharge destination, patients may undergo clinical rehabilitation or home rehabilitation to recover from the disability. The discharge rehabilitation usually takes a period of months or years, which covers the sub-acute and chronic phase. From the standpoint of rehabilitation period, obviously the discharge rehabilitation is the dominant (that is, more time-consuming) process over the whole post-stroke recovery process, compared to the acute stroke hospitalization. Furthermore, previous rehabilitation studies have suggested that the first weeks-to-months is critical for the behavioral recovery in the long term [23–26]. Additionally, drug therapy may be applied for post-stroke rehabilitation.

2.2.1 Clinical and Home Rehabilitation

In clinical setting, individuals post-stroke after the acute phase may take some comparatively high-intensity, task-specific, and goal-oriented therapies for rehabilitation. Since the clinical rehabilitation is led, guided, and monitored by professional therapists and caregivers, patients can obtain efficient support, care, and training sessions, which are usually significantly meaningful and effective for the improvement of patients' motor recovery and functional

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ability [25]. However, there are still some non-negligible problems underlying the present clinical rehabilitation. First of all, currently most treatments and care are provided for post-stroke patients according to clinical observation and/or patients' self-report questionnaire. Therapists conduct the clinical observations and give the subsequent assessments based on some rating scales (e.g., Functional Independence Meaures (FIM), Barthel Index (BI), National Institute of Health Stroke Scale (NIHSS), and Fugl-Meyer Assessment (FMA), and Motricity index [27–29]) depending on their own experiences. As a consequent, it is possible that therapists with different professional experiences give difference scores even on the identical physical performance, which definitely leads to subjective and inaccurate evaluations. Similarly, at the same time patients may give inaccurate self-reports due to their memory, misunderstanding and emotions [30]. All these highly possibly inaccurate evaluations may finally result in a slow-rate, low-efficiency and even worse recovery. Furthermore, this existing approach of clinical assessment is time-consuming and imposes substantial burdens on caregivers and society.

Post-stroke patients in sub-acute and especially chronic stroke stage may also discharge home from the rehabilitation center, considering their motor functionality, preference for home rehabilitation [31], and accessibility to healthcare [32]. On one hand, compared to the clinical setting, patients in the familiar environment, i.e., home, have the feeling of repersonalization, autonomy, and happiness, which might contribute to better rehabilitation outcomes [33, 34]. On the other hand, patients in the home setting, without professional care, have to face the substantial psychological challenges (e.g., anxiety, uncertainty, and depression) and physiological challenges (e.g., slowed life, loss of coordination and posture instability) by themselves. This may further have a negative effect on their participation and quality of life. More importantly, patients at home may not follow the instructions and not adhere to the training program very well [35, 36], such as the phenomenon of learned non-use. This discrepancy can be enlarged by the subjective, inaccurate self-reports of patients. Therefore, a system that enables quantitative monitoring and supervised learning is required for a better home rehabilitation outcome.

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2.2.2 Wearable Technology for Stroke Rehabilitation

Recently with the rapid advancement in technologies such as the manufacture micro-electromechanical systems (MEMS), sensor technology, data analysis, communication technology and material science, wearable technology is increasingly contributing to stroke rehabilitation as a role of robot-assisted therapy and/or sensing and monitoring, which together ensure a promising future of telerehabilitation. The telerehabilitation system can remotely, continuously monitor patients' health status (i.e., stroke severity), return the vital information to rehabilitation center, professional therapists and patients' families, and thus provide patients efficient intervention if required. This will enable patients a life with more safety, independence, control and participation in activities, and moreover, will relieve the pressure on the healthcare system and professionals as the result of a more effective care.

When provided appropriately, the robot-assisted therapy can outperform the conventional therapy in the rehabilitation outcomes, due to the standardized training environment, the ability to increase therapy intensity, and the adaptive support [37]. In terms of the flexibility of exoskeleton, there are broadly three types of rehabilitation robots (Figure 1 [37]), for example, the firstly proposed planar manipulandum MIT-MANUS in 1989 by Krebs and Hogan [38], the robot ARMin for three-dimensional, task-specific therapy by Klamroth in 2014 [39]. More rehabilitation robotics have been summarized by review papers [37,40]. These assisting robots fundamentally function by modulating the interaction between patients and devices and/or the output impedance of devices. Rehabilitation robots bear great potential for continued training at home and thus a more successful home rehabilitation.

Moreover, the wearable technology makes a significant, distinct contribution to stroke rehabilitation, with the ability of continuously monitoring patients' health status with respect to motor disability and motor recovery. Nowadays the wearable sensors are becoming more and more popular for monitoring and tracking the ongoing rehabilitation process, due to its minimally-invasive, minimally-unobtrusive, and comfortable properties [41]. Compared to the ambient sensors, which are generally embedded on some fixed places (e.g., door, refrigerator and wall) and constrained to that specific environment such as home, wearable

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sensors are not constrained to specific space. Notably, the development of key technologies such as low-power wireless communication, MEMS and material science is enabling the mobile ability of sensors, which makes it possible for stroke individuals to have a greater extend of activity and participation through continuously safety monitoring and therefore to have better quality of life. For example, based on sensor fusion Lorussi et al. developed a wearable sensing platform in the form of shirt, trousers, glove and shoe, to monitor physical activities and evaluate motor ability in stroke patients. This wearable unit showed capability in monitoring reaching activities, gait and grasping activity [42]. Another widespread, popular wearable sensing system is the mobile phone, which can include multiple sensors such as accelerometer, gyroscope, barometer, and GPS. A family of researchers have been studying to apply this smartphone to monitor mobility-related activity of post-stroke individuals outside the clinical setting [43, 44].

Among the wearable sensors, a new generation of electronic device, designated by Inertial Measurement Unit (IMU), has emerged and been gaining popularity in human ambulatory motion analysis of tele-rehabilitation. An IMU sensor can combine multiple sensors, i.e., tri-axial accelerometer, tri-axial gyroscope, and tri-axial magnetometer. The accelerometer measures segment linear acceleration, which is integrated twice over time to find the segment position with respect to the initial position. The gyroscope measures the segment angular velocity which is integrated to find the segment orientation with respect to the initial orientation. The additional integration of magnetometer enables to measure the magnetic direction. Therefore, IMU sensors can be used to measure velocity, position and orientation, gravitational force and the magnetic field. During its application, filter processing may be applied to eliminate the drift errors by gyros, in order to improve the accuracy. Presently IMU sensors also have developed into a wide range of response rate, e.g., 50 Hz, 128 Hz and 200 Hz. Moreover, IMUs may be equipped with wireless technology, a secure digital (SD) card or even an output pin logged by wire to a base station [45]. Due to its advantages of being accurate, cost-effective, minimally-intrusive, portable, and comparatively unlimited in workspace, until now, a wealth of researches in stroke rehabilitation have applied IMUs to monitor and collect human continuous movement data. These studies cover human upper-extremity motion [46–50], and lower-extremity motion [45, 51–54], with the aim to evaluate

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and/or identify human motion, provide feedback on motor performance, and design assistive robotics.

2.2.3 Implication for Future Stroke Rehabilitation

With the increasing pressure on healthcare system and professional therapists caused by chronic stroke, the tele-rehabilitation technology holds a promising future for an efficient and effective post-stroke rehabilitation, especially the home rehabilitation. In tele-rehabilitation, patients' health status related to stroke disability would be continuously monitored by non-invasive wearable sensors, e.g., smartphones, IMUs, and returned to the rehabilitation center, which can provide interventions and/or help accordingly. Meanwhile, individuals with stroke can participant in the training program at home in terms of the robot-assisted therapy. Therefore, patients with stroke can have a life of more safety, independence and control.

2.3 Adaptive Intervention

Adaptive intervention has emerged as a new promising perspective on the prevention and treatment of chronic diseases, such as drug abuse, cigarette smoking and obesity [55–58]. Based on the pre-specified decision rules, these interventions adaptively assign cost-effective components and/or dosage of treatment across individuals and within individuals across time, according to the assessment of individual key characteristics (e.g., level of parental functioning in Fast Track program [59]), referred as *tailoring variables*. The decision rules are capable of linking each individual tailoring variable with a specific intervention at any time point. Because these interventions are delivered when and where needed, they can be called just-in-time adaptive interventions (JITAIs). Compared to the conventional fixed intervention, which assigns a single composition and dosage to all participants and may not meet all needs and therefore cause negative effects, JITAIs may reduce the negative effects, reduce the waste of resources, increase participants' compliance, and finally enhance the potency of interventions [60].

Naturally speaking, adaptive intervention make use of interventions to influence the dynamics of disease progression processes and optimize the treatment results. This is very

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similar to what control engineering principles are doing: how to influence a *dynamical system* in order to regulate it and thereby achieve more desirable outcomes [61]. Stemmed from this similarity, the last 20 years have seen an increasing interest in the design and implementation of adaptive behavioral intervention with the approaches of dynamical systems and control engineering methods to increase and optimize interventions [56, 60]. For example, with the integration of a mechanistic energy balance model with Theory of Planned Behavioral models, Dong et al. constructed a dynamical systems model to describe how a behavioral intervention can influence weight gain during pregnancy [57]. Similarly, based on an existing empirical model of smoking and craving cigarette, Timms et al. implemented an adaptive pharmacological smoking intervention algorithm with the combination of user behavior in order to promote smoking cessation [58]. Previous researches have shown that the intensity of training and its time from stroke onset may play decisive roles in determining the long-term motor recovery for post-stroke patients. Therefore, from the standpoint of the requirements of time-varying treatments and also the chronic nature of human behaviors, the adaptive intervention holds great promise to optimize the chronic post-stroke rehabilitation process.

To design a JITAI for the prevention and treatment of learned non-use during chronic stroke rehabilitation, it is fundamental that there is some representative dynamical systems model and tailoring variables. More specifically, the dynamical systems model should be sufficient to model the different but time-varying behaviors between paretic and non-paretic limb for each individual during the ongoing recovery process. The tailoring variables should be sufficient to represent the individual key features, that is, severity of hemiparesis.

2.4 Dynamical System and Identification of Post-Stroke Severity

In mechanical perspective, there have been numerous investigations on human musculoskeletal system in terms of the mechanical properties, dynamics and performance. For example, Sinkjaer et al. studied the mechanical response (i.e., muscle stiffness) of normal human ankle dorsiflexors at different levels of voluntary contraction [62]. And a large number of

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researchers have conducted studies on the viscoelasticity of human upper limb, especially the elbow joint [63–66]. There are also a list of conceptual studies on human biomechanics [67, 68]. Generally speaking, the mechanical properties of human musculoskeletal system is very complex, influenced by the task, environment, motion, limb posture and other factors simultaneously. For the dynamic analysis of normal human movements, it has been shown the joint dynamics can be simplified as a second-order, underdamped system [69, 70]. Furthermore, people have been trying to understand the mechanisms and criteria underlying human natural performance and movements, for example, Hogan proposed the minimal jerk model for a class of human voluntary movements in 1984 [71]. Later in 1989 Uno et al. proposed the minimum torque-change model that controls human multijoint arm movement [72]. Recently in 2007 Ren et al. employed the minimal energy criterion to simulate normal walking [73]. However, all these minimal principles showed their limitation in modelling [74]. In conclusion, due to the complexity of human musculoskeletal system, currently most of the related theories are condition-dependent, have their limitations, and/or remain unvalidated experimentally. Notably, there is far less such investigations in post-stroke behaviors and movements.

Indeed, there have been a series of studies on the understanding and evaluation of post-stroke disability in term of kinematics or kinetics. The kinematic features can include peak velocity, peak acceleration, range of motion (ROM), movement smoothness, movement speed, and motion time, etc [75, 76]. The kinetic features can include maximum voluntary contraction (MVC), muscle strength, and joint torque patterns, etc [77–80]. For example, Mirbagheri and Rymer showed that with the logistic regression model the features such as active ROM, MVC and peak velocity are good at predicting motor recovery of stroke patients in one year [75]. Michielsen et al. quantified the nonuse for chronic stroke patients in daily life through the motion time and intensity [76]. Dewald and Beer found abnormal joint torque patterns in paretic upper limb of patients with hemiparesis during shoulder and elbow activities [80]. These evaluations are merely based on the signals collected by sensors, which ignore the potential connection between the kinematic and kinetic features. These evaluation approaches are usually associated with the problems of massive sensor deployment, constrained application to lab/clinical setting, and low patient throughout rates.

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Considering the future clinical application of adaptive intervention in chronic stroke rehabilitation, a physical model is required that is able to evaluate and identify the severity of individual post-stroke from a dynamical systems perspective, with the paretic limb being continuously monitored by the convenient,non-invasive, wearable sensors, e.g., IMUs, in either clinical or ambient setting.

2.5 Markov Decision Process (MDP) in Dynamic Limb Choice

2.5.1 Role of MDP in Human Health Care Systems

Recent years, the approach of simulation modelling is making more and more significant contributions to the development of human healthcare system. Especially in the situations that it is impossible and/or time-consuming and labor-intensive to conduct direct experiments on human subjects, for example, longitudinal date related to chronic diseases (e.g., depression, chronic stroke), simulation modelling shows an overwhelming advantage of cost effectiveness in assessing the effects of treatments. With simulation models, people attempt to replicate their interested clinical trails, capture and understand the clinical system dynamics/behaviors, and thus have some insight into our decision making in interventions for healthcare [81]. Broadly speaking, there are four types of modelling frameworks: decision trees, Markov models, discrete event simulation, and system dynamics. Among these four approaches, Markov modelling is usually the preferred method across areas and illness [82]. The Markov model simplifies the interested clinical events into that patients are always in one of health states (referred as Markov state) and that the disease progression is represented as transitions from one state to another. As a result, Markov models are particularly suitable to model repetitive events and also incorporate temporal details over a long-period time [83–85]. As with other other simulation models, there are pros and cons for Markov models. The major weakness for Markov families is due to the lack of memory (called *Markov property*), that is, they may not track patients' disease history properly.

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In terms of the controllability of system and the observability of system states, there are four common Markov models, that is, Markov chain, Hidden Markov model (HMM), Markov decision process (MDP), and Partially observable Markov decision process (POMDP). The latter two models can be applied to determine the optimal sequential decisions in dynamic environments. As the special cases of *reinforcement learning* (RL), fundamentally speaking, either MDP or POMDP is a learning system that adapts its behavior in order to maximize some desired signal from its environment [86]. Compared to POMDP, MDP assumes that the system states are fully observable, which is a definitely ideal case, in terms that there is always existing noise and uncertainties in our agent-environment interface. However, if the relatively simplified MDP is capable of capturing enough of the underlying relationships and thus discriminating among actions, the simpler model, i.e. MDP, may be suggested considering that simpler models often provide greater inside into the important underlying relationships and remove some obfuscation inherent in over-detailed models [81]. In other words, choosing MDP or POMDP is dependent on the specific tasks.

2.5.2 Application of MDP in Human Health Care Systems

There have been many studies on the applications of Markov models into human health care issues. Basically, there are two types of goal orientations: (1) to evaluate and compare the effects of treatments or to estimate the dynamics of disease progression, in terms of the potential function of prediction; (2) and to provide the optimal treatments in terms of the potential function of control. These cover a wide range of illness such as depression, Alzheimer's disease, schizophrenia, and chronic stroke [82, 87]. For the first application, people primarily focus on the the evaluation of the cost-effectiveness of the pharmaceutical and/or non-pharmaceutical treatments, or to estimate the key varying features during the dynamic disease progression, with some real serial periodic or longitudinal data. For example, there have been a number of cases that people applied the Markov models to compare the outcomes and costs of different treatment for patients with chronic schizophrenia. In these models, generally, researchers require to define the health states which are context-dependent, and rewards which are usually a combination of measures of interests such as treatment-emergent side effects and treatment costs [47, 88, 89]. Patten and colleagues estimated the

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prevalence, incidence and episode duration for the disease of major depression in national population based on a Markov Model, in which there are two health states, depressed and nondepressed [90–93].

There are also a number of case studies on the second application in providing optimal treatments. For example, Magni et al. applied the MDP approach to the problem of mild hereditary spherocytosis, characterized by a chronic destruction of red blood cells, to choose the optimal time for intervention. They defined the state of patients according to the severity of gallstone and the presence (or years since removal) of spleen and estimated the transition probabilities based on the previous studies. With the overall objective to maximize the patients' quality-adjusted life years, they derived the optimal time of interventions [94]. Similarly, Kan et al. proposed a real-time system, with the combination of a robotic system and POMDP, that automatically modifies exercise parameters (i.e., target position, resistance level and stopping exercise) according to the individual specific needs and abilities, in order to guide post-stroke patients through a reaching rehabilitation exercise [95]. More recently, Bennett and Hauser developed an general artificial intelligence framework combing MDPs and dynamic decision networks to determine the optimal clinical decisions. Using real-world patient data, this AI framework outperformed the traditional treatment-as-usual models in terms of patients outcomes and cost [96].

2.5.3 MDP in Post-Stroke Rehabilitation Systems

Particularly, the approach of Markov modelling has also gained popularity in the field of post-stroke rehabilitation recently, with the roles of planning and control we mentioned previously, for example, predicting the dynamics of stroke disease [97,98], evaluating the cost-effectiveness of treatments [99–103], and furnishing the optimal interventions [95, 104, 105]. Fundamentally speaking, all these studies are constrained within one or several predesigned treatment strategies and consequently are associated with some potential limitations. One one hand, while these treatments are the possible approaches, but may not be the optimal one from the perspective of cost-effective health care system. On the other hand, even in some exercise program, stroke patients' adherence is less than ideal [36, 106, 107], which further worsens the recovery outcome. Therefore, a systematic exploration of the interaction

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between stroke patients and health care system is required for a cost-effective intervention for stroke rehabilitation.

Interesting, people in the field of stroke rehabilitation have been spending a lot of time on construction of cost-effective intervention for recovery. Numerous studies have been conducted to figure out the factors that influence (motivate or prevent) patients' adherence to the exercise program. Besides the training program, people found that there are other latent decisive factors such as the desire to improve health, motivation level, and musculoskeletal issues, possibly influencing the recovery outcomes of chronic stroke individuals [35, 36, 108]. However, we human is a really complicated dynamic system, whose behavior can be influenced by a physiological and/or psychological signal. People in different domains have always been trying to explain and predict human behaviors, for example, the self-efficacy model [109] and the social cognitive theory (SCT) [110, 111]. However, all these models showed limited ability in explanation and prediction in patients' behavior of non-adherence. Obviously, there is a deficient understanding of the underlying mechanism of multiple primary factors on rehabilitation progression from a comprehensive, systematic perspective.

Considering the nature of MDP that a learning system adapts its behavior in order to achieve some goal(s) in an environment, we may apply the approach of MDP to quantitatively understand the patients' behaviors during chronic stroke rehabilitation process. We believe that a better understanding of this systematic mechanism (e.g. the weight or relative influence of each factor) may help to construct more specific, effective, and personalized interventions for individual post-stroke rehabilitation, which is especially meaning for clinical applications.

Therefore, we use MDP to explore which factors are "driving/leading" patients to show the behavior of dynamic limb choice, or, suppression of paretic limb choice. The factors would be the simplified quantification of individual psychological and physiological states during the post-stroke rehabilitation process. Meanwhile, the evaluation of patients' physiological state is based on the upper-extremity physical model we developed.

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2.6 Summary

In summary, there are two main challenges for the implementation of a cost-effective intervention for stroke rehabilitation. Firstly, an objective, accurate, effective and convenient way to monitor and evaluate patient' post-stroke time-varying motor disability is required during rehabilitation process, especially in ambient/home environment. Secondly, in order that patients could get the optimal rehabilitation recovery in future, given patients' progression known, we need to find out the corresponding type and components of treatments that could be provided for patients. Facing these two challenges, in the first step, we developed a human upper-extremity dynamical system model to evaluate patients' motor performance with the input of kinematic information which can be collected by minimally-invasive IMUs. In the second step, we applied the approach of Markov decision process to understand and explore the factors influencing patients decision making of limb choice during the recovery process. Based on the modelling results, we further provided some suggestions for potential cost-effective intervention for stroke rehabilitation.

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Chapter 3

Methodology: Development of Upper-Extremity Dynamic Model

Without a comprehensive and complete understanding of the complicated nature of human motor systems, up to now, there is still no such powerful model that is capable to exactly describe and explain the motions of human musculoskeletal system. In this dilemma, based the existing knowledge on human movements and the primary principle of model reference adaptive control (MRAC), in this section, we develop a dynamical system model to mimic the movement dynamics and to further evaluate the corresponding motor performance, for both healthy and post-stroke individuals.

3.1 Movement of Shoulder Flexion

Considering the extreme complexity and remaining uncertainty in the underlying mechanisms of human musculoskeletek system, we firstly conduct our investigation of the dynamical system model for a very simple, single joint movement, shoulder flexion, as shown in Fig. 3.2 (a). During shoulder flexion, people flex the upper extremity from the home position 0° to the goal position 180°, with the elbow fully extended throughout the total range of motion, that is, with the elbow always at 0° [112].

As the result of complicated mechanisms of human dynamic movements, researchers have been studying human movements with reasonable simplification and specific experimental

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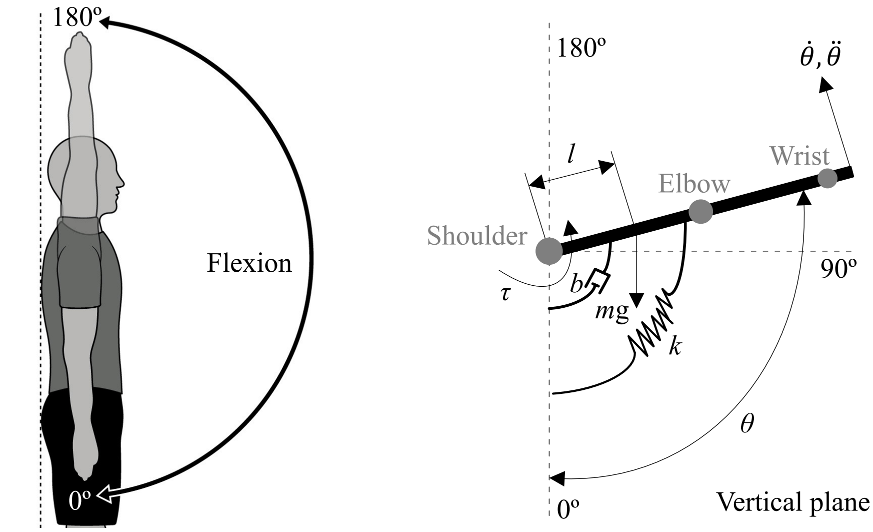

Figure 3.1: Schematic representation of shoulder flexion and the underlying mechanism

designs, e.g, constraints on body segments, speed and range of motion, external perturbation, and so on, which determines the complexity (e.g., degree of freedom) of human movements and furthermore the difficulty in understanding the underlying mechanisms. From a physical standpoint, a majority of studies on the human upper extremity movements in the horizontal plane have verified the simplification of human arm into a second-order, underdamped system [69–72]. With respect to the universal primary mechanisms underlying joint dynamics of peripheral neuromuscular control systems [113], it is sensible to model the human upper extremity in a shoulder flexion task as a second-order, underdamped system. Additionally, different from those previous study of multijoint arm movements where the elbow joint can be at a nonzero position and accordingly the degree of freedom (DOF) is no less than two [69–72], our study requires participants to perform the task with their elbow joint always at 0 °. Consequently, the task of shoulder flexion is a single DOF motion, the system of human upper limb rotating around the shoulder joint in a sagittal plane. Therefore, we propose a single DOF, second-order, underdamped pendulum-based mechanical system to represent and mimic the dynamics of human upper limb in a sagittal plane during shoulder flexion, as plotted in Fig. 3.2 (b). We decribe the corresponding dynamics with the equation of motion

$$\tau - mgl \sin\theta - k\theta - b\dot{\theta} = J\ddot{\theta} \tag{3.1}$$

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where θ, $\dot{\theta}$ and $\ddot{\theta}$ are the varying angular displacement, angular velocity and angular acceleration of shoulder joint, i.e., human arm, in the task, respectively. The parameter m is the total mass of human upper extremity and g is the gravitational acceleration. The term l denotes the position of center of mass (CM) of upper limb with respect to shoulder joint. The parameter J is the moment of inertia of upper limb about the axis which crosses the shoulder joint in a sagittal plane. Additionally, Coefficients k and b represent the joint stiffness and damping coefficient of human arm during the motion. Finally, the term of τ is the resultant joint torque which actuates and drives the upper limb rotation. In summary, during the dynamical process of shoulder flexion, the total actuating torque needs to overcome the resisting effects caused by the elasticity property, viscosity property and gravity of upper extremity musculoskeletal system and to accelerate/decelerate it to the goal position, simultaneously.

3.2 Literature on System Coefficients

In this paragraph, we will summarize the previous studies, experimental and/or analytical investigations on the factors included in the formula given in previous subsection.

3.2.1 Inertia Quantities

The inertia quantities, m, l and J, in Equation 3.1 are dependent on the mass and mass distribution of human upper limb. Researchers have been applying methods of both experimental procedures and mathematical modelling to approximate these values for individual body segments or for the body as a whole in different positions [114–120]. However, due to the difference in study specimens (i.e., cadaver or in vivo) and populations (e.g. age, body weight, fat mass), there is still no unified and practically applicable method to evaluate these inertia quantities for individuals in vivo. Because the anthropometric parameters reported by Hall [120] are more accepted, in our study we approximate these individual values [m, l, J] based on the relations suggested in [120] and participants' total body weight and height we measured during experiments. Here is the detailed computation.

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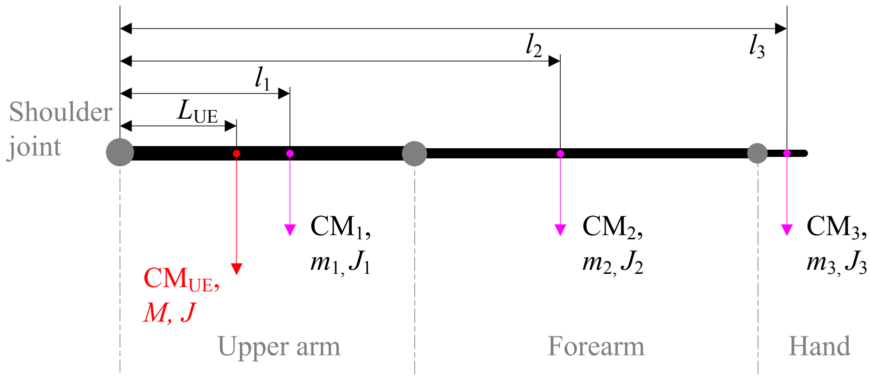

Figure 3.2: Geometry and inertia of human upper extremity

$$L_{UE} = \frac{m_1 l_1 + m_2 l_2 + m_3 l_3}{M} \tag{3.2}$$

$$J = \sum_{i=1}^{3} J_i + m_i (l_i - L_{UE})^2 \tag{3.3}$$

where m_1, m_2 and m_3 are the mass of upper arm, forearm, and hand, respectively. l_1, l_2, and l_3 represents the segmental center of mass (CM) locations measured from the shoulder joint. Parameters J_1, J_2 and J_3 denote the moment of inertia with respect to an axis passing through their individual CM in a coronal plane for each segment. These segmental inertia quantities, m, l, and J, are approcimated by the information in [120]. The total mass M of human upper extremity is simply a summation of these three segmental mass. The location CM_{UE} of upper extremity is calculated by Equation 3.2. The moment of inertia J for the whole human arm corresponding to the axis passing through CM_{UE} is the sum of moment of inertia of each body segment corresponding to the same axis, as the Equation 3.3.

Furthermore, the limb configuration is the dominant factor in its inertia. During shoulder flexion, the change in the configuration of human upper limb is negligible, that is, the elbow always being fully extended. Therefore, we assume that the moment of inertia J for the total human upper extremity constant over the the whole movement.

3.2.2 Joint Stiffness

Our human musculoskeletal system performs a task by the synergism of muscles, tendons, ligaments, connective tissues. The coefficients k in Equation 3.1 represent the stiffness

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component of the equivalent mechanical impedance of these structures during shoulder flexion. Here we define k as the amount of resistance to joint torque per unit of angular displacement change, which is the same to the definition of apparent stiffness suggested by Latash [67]; Unlike the stiffness in passive elastic object, the joint apparent stiffness is much more complicated in the mechanism. It depends not only on the arm posture and joint angular displacement, but also on the motor task, application of external loads, movement speed and measurement time [62, 65–68, 121]. In our experiments, there was a visible difference among participants' angular velocities, even within groups. The mean angular velocity of healthy controls and stroke patients in each trial varied in the range of 60-218$°/s$ and 14-106$°/s$, respectively, both of which covers slow, moderate and fast movements [65]. Additionally, the range of motion in the shoulder flexion task approaches the limits of shoulder joint. These two factors, movement speed and range of motion, definitely influence the magnitude of joint stiffness k. However, considering the complicated variability by these factors and the primary role of our dynamical model in adaptive intervention for stroke rehabilitation, we simplify our joint stiffness k during shoulder flexion into the elastic stiffness which depends on the magnitude of joint displacement and does not depend on time.Biomechanically speaking, muscles make the dominant contribution to the mechanical properties of a joint. Therefore we assume that the equivalent joint stiffness linearly increases with the angular displacement magnitude in our experiments [63, 64, 122]. Previous studies on the stiffness of shoulder and/or elbow joint, mostly in the horizontal plane, suggest a wide range of values from 0-40 Nm/rad [65]. Furthermore, the arm impedance reflects the dynamic interaction between the limb and the environment [123, 124], which indicates a floor value for joint stiffness. Therefore, we initial assume k to be dynamical and varying according to

$$k = \begin{cases} k_a & \theta \leq \theta_0 \\ k_b(\theta - \theta_0) + k_a & \theta > \theta_0 \end{cases} \tag{3.4}$$

where $k_a = 5$, $k_b = 6$, and $\theta_0 = \dfrac{\pi}{3}$ (Sinkhaer et al. found a similar relationship for the total ankle stiffness [62]).

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3.2.3 Joint Viscosity

The coefficients b in Equation 3.1 represent the damping component of the equivalent mechanical impedance of the arm in the shoulder flexion task. We define the joint damping coefficient b as the incremental amount of resistance to joint torque per unit of joint angular velocity change. Up to now, from a mechanical perspective, it has been widely accepted that our human musculoskeletal system is an underdamped system and that the damping coefficient b increases as the displacement increases. Literately speaking, there are three main viewpoints on this dynamic joint viscosity property (i.e., damping coefficient b or damping ratio ξ, $b = 2\xi\sqrt{Jk}$): (1) The ratio between b and stiffness k is nearly constant for muscle torques in the range of 3.0-30.0 Nm [125]; (2) The variation of ξ during movements is negligible [126, 127]; (3) The damping ratio ξ varies in the range of 0.1-0.6 [65, 128]. Empirically speaking, We conducted the simulation experiments to investigate the influence of ξ on the actuating joint torque τ. Satisfying an underdamped system or a lightly overdamped system, that is, $0.05 \leq \xi \leq 1.5$, we tried different expressions for ξ as functions of angular displacement θ, including constant value, linear, quadratic and natural exponential. We found that there was very small variation of the resultant torque. In this case, we assign the damping ratio to be a typical constant value, 0.4, in the simulation of the whole motion. even we made a great adjustment, the resulted influence on τ is negligible. Therefore, we express the damping coefficient b as

$$b = 2\xi\sqrt{Jk} \tag{3.5}$$

where $\xi \equiv 0.4$.

3.3 Torque-Based Approach to System Identification

As discussed previously about the equation of motion, Equation 3.1, of human upper limb, either the synthesis of physical and biological principles or the system parameters (i.e., [m, l, J, k, b]) are simplified and not accurate. Moreover, in our study the resultant joint torque τ cannot be directly measured. Merely with the access to participants' kinematical

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information, $[\theta, \dot{\theta}, \ddot{\theta}]$, we therefore apply the approach of system identification and implement a reference submodel to evaluate participants' motor performance and thus to identify the characteristic of interest, motor functionality (or stroke severity) for both healthy controls and post-stroke patients. For the dynamic analysis of each individual, the reference model is constructed by an input of reference motion and the identical plant model of upper limb.

Although there are a number of candidate models for the formation of simple human movements in terms of different performance criteria, e.g., the minimum jerk [129], the minimum torque [72], and travel cost [130], the ongoing research indicates that these trajectory-formation models usually have limited explanatory power, and that goal-directed movements actually make use of multiple strategies [131–133]. In this condition, it is more convenient and economical for us to choose the simplest motion, constant-velocity motion, as the participant-specific reference motion. In each trial, participants flexed from the home position to the target position and then back to home position. Participants, especially healthy controls and patients with mild stroke, showed visually symmetric trajectories, as showned in Fig. 3.3 (a). In the reference model, participants are assumed to perform shoulder flexion from the home position θ_0 to the required goal position θ_{goal} at a positive, constant velocity within the half motion time and to perform shoulder extension at a negative, constant velocity within the rest half motion time. If the participant paused at the maximal position during experiments, there will be an identical-duration pause in the reference motion. The motion time is defined as the period when the angular velocity θ is greater than 0.1 rad/s. We therefore developed a straight line approximation of the participant trajectory profile, making use of the total duration and amplitude of the experimental velocity profile.

3.4 Implementation of Dynamic System Model

With the combination of the upper-extremity plant model and the torque-based identification approach presented previously, we build the whole dynamical system model (Fig. 3.4) in Matlab/Simulink environment, which is aimed to detect and evaluate motor performance

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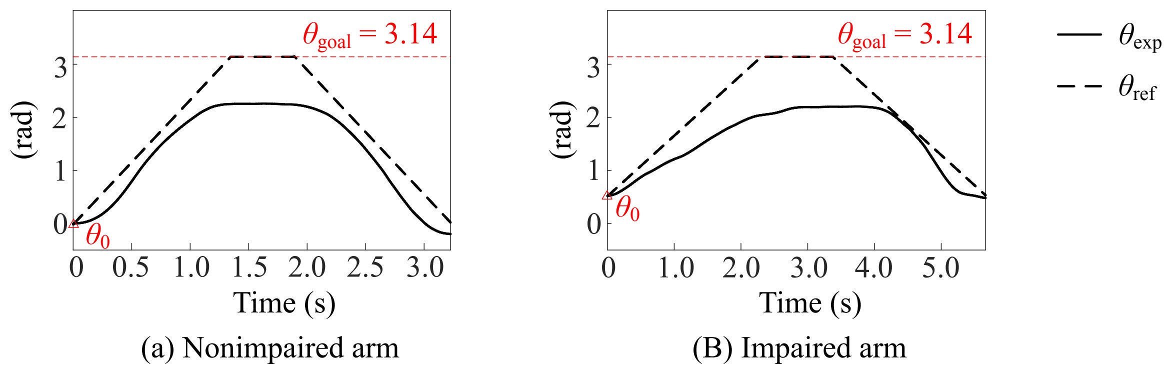

Figure 3.3: Examples of experimental trajectory (solid curve) and the corresponding reference trajectory (dashed curve) for non-impaired and impaired arm

for both healthy and post-stroke individuals in a shoulder flexion task, although not to exactly describe the motion dynamics.

First of all, we model the physical system of human upper extremity using Matlab/Simscape to mimic arm dynamics during shoulder flexion. Subsequently, we derive the inverse dynamic model and assess the corresponding joint torque for kinematic information. Through the comparison between torque curves from the actual motion and the reference motion, we evaluate participants' motor ability. As we explained before, the system of upper extremity in this task can be simplified into a single-joint mechanical system in two dimensions, considering the influences of elasticity, viscosity and gravity on the limb during movement, as shown in the bottom panel of Figure 3.4. The limb and shoulder joint are modelled as an inertia (block labeled as "Upper Extremity"), with participant-specific values for mass and the inertia tensor, attached to a revolute joint (red block labeled as "Revolute Joint"). The translation transformation (blue block labeled as "Trans 1") is utilized to account for the distance of the center of mass to the shoulder joint. For joint stiffness and joint viscosity, a MATLAB function (red block labeled as "TorqueBK") was built to calculate the torque caused by the components of stiffness and viscosity, with outputs applied to the revolute joint as a resultant external force. Meanwhile, the initial state, angular displacement, and velocity, can be specified in the block of the revolute joint. In summary, using motion data-derived kinematics (θ $\dot{\theta}$ $\ddot{\theta}$), the plant model outputs the actuating torque τ. The whole dynamical system model is represented in the top pane of Fig. 3.4, and includes the inverse dynamics process and the comparison of actuating torque curves. This inverse

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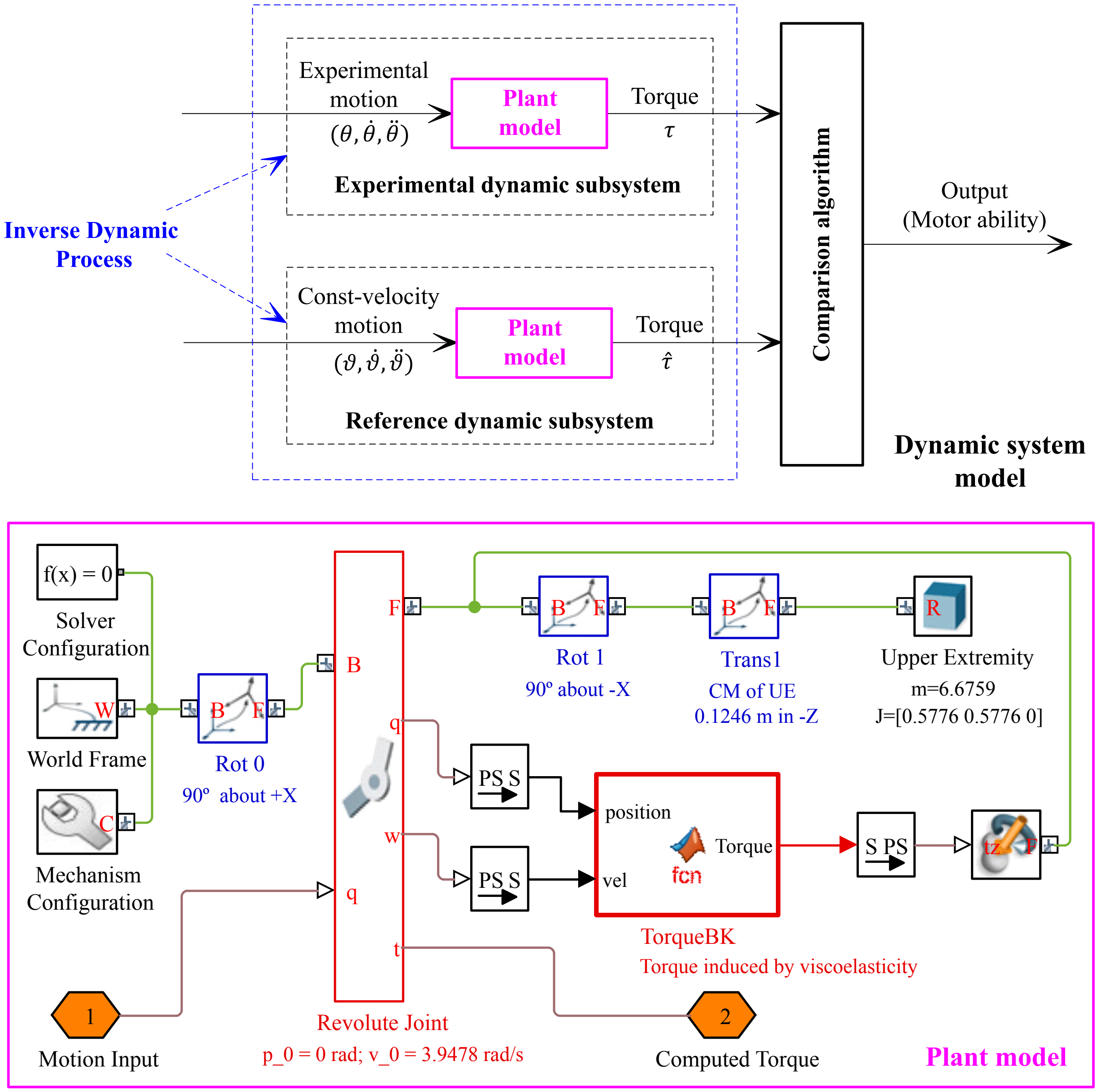

Figure 3.4: The arm plant model (bottom) and the whole dynamic system model (top) during shoulder flexion

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dynamics process refers to two dynamic models simultaneously; the experimental subsystem (the upper layer) and the reference subsystem (the lower layer). Together, these represent the inverse dynamics of the arm plant model actuated by participants' experimental motion and the reference motion, respectively. Given individual movement data, this system model is capable of quantitatively evaluating and generating motor ability.

Therefore, provided with the kinematic information of an individual during shoulder flexion, our dynamic system model is able to evaluate this participant's motor ability quantitatively, although not exactly describing his/her movements. We hypothesize that a more severe post-stroke disability would lead to a more obvious difference in output torques between the experimental model (the plant model with the input of actual experimental motion) and the reference model.

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Chapter 4

Experiments and Discussion

In this chapter we validated and evaluated the performance of the dynamical system model we developed in Chapter 2 with the experimental data. Furthermore, we investigated its potential clinical application.

4.1 Participants

Recruitment and screening of participants took place at University of Tennessee Medical Center, Knoxville, TN and University of Tennessee, Knoxville, TN, according to the standards of the University of Tennessee Institutional Review Board. Five post-stroke patients (3M, 2F, 64.6 $\pm$ 21 years) and six healthy controls (4M, 2F, 25.7 $\pm$ 3.7 years) participated in our study. All the stroke patients met the following criteria: (1) absence of cognitive impairment; (2) ability of performing even limited shoulder flexion with the elbow fully extended. None of the healthy controls have the history of stroke before. All the participants are right-hand dominant.

4.2 Experimental Design

As we discussed before, as the result of the extreme complexity in human musuloskeletal system, we currently investigate the system model for the human single-joint movement, shoulder flexion. Participants performed the task with their own comfortable speeds in

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cross-sectional designs. In each session, participants wore the monitoring sensors, inertial measurement units (IMUs) to capture their motion at 128 Hz. Each IMU consists of a tri-axial gyroscope, an accelerator and an magnetometer. For the post-stroke group, shoulder flexion is one of the individual tasks in the Fugl-Meyer Assessment of Upper Extremity (FMA-UE) for the measure of upper-extremity motor impairment. Before the assessment, therapists attached four IMUs to the fixed points of patients' upper arms and forearms with elastic bandage, with z-axis of each IMU perpendicular to the sagittal plane. Provided with clear and concise instructions, patients performed each task firstly by their non-paretic arm once and then by their paretic arm three times. The best performance among these three repeats was scored. Meanwhile a video camera was utilized for recording and off-line data processing. Specifically, patients in a sitting state started shoulder flexion with the full eblow extension from a home position (nonzero, the arm rightly not being physically supported) to a goal position (90°, 180° or the maximal position they could arrive). One case that a patient was performing shoulder flexion is shown in the left side of Figure 4.1. For the control group, participants performed the shoulder flexion ten times by their dominant arm and later ten times by their non-dominant arm. Before performing the task by the manipulating arm, two IMU sensors were attached to the fixed positions (i.e., the upper arm and forearm) of this arm with elastic straps. Then in a standing state, participants performed shoulder flexion with this arm, as shown in Figure 4.1 (right).

Figure 4.1: A post-stroke patient (left) and a control subject (right) performed the task of shoulder flexion

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In later experimental analysis, one full trial of shoulder flexion includes the motion from the home position to the target position and also back to the home position.

4.3 Model Validation

In Fig. 3.4, the input vector $\dot{\theta}$ is the band-pass filtered angular velocity between 0.01 and 10 Hz, which is initially collected by the rate-gyroscope of the wrist IMU. The other input vectors, θ and $\ddot{\theta}$, can be obtained by numerical integration and differentiation of $\dot{\theta}$, respectively. With the vector $\mathbf{\Theta} = [\theta; \dot{\theta}; \ddot{\theta}]$, the inverse dynamics model provides the joint torque.

To confirm the ability of our model to mimic the dynamics of the UE during shoulder flexion, we actuated the forward dynamical system with the derived torque $\tau/\hat{\tau}$ in Fig. 3.4. The results of a subset of validation experiments are plotted in Fig. 4.2, which includes the inverse and forward dynamics of two arms from one control subject (Fig. 4.2a) and one post-stroke participant (Fig. 4.2b). In each figure, the top and bottom panels show the trajectory and torque curves, respectively, during these processes. Take, for example, the left column of Fig. 4.2a, which is associated with the trial of the control subject performing shoulder flexion by the non-dominant arm, his/her actual experimental trajectory θ_{exp} and the corresponding time-scale reference motion θ_{ref} are plotted (black and red curves, respectively) in the top panel. With the input of experimental and reference motion vectors, the inverse dynamical model derived from joint torques, τ_{exp} (black dotted curve) and τ_{ref} (red dotted curve), are plotted in the bottom panel. Driving the forward model with these two torque vectors results in derived forward trajectories, $\theta_{exp,forw}$ (yellow dotted curve) and $\theta_{ref,forw}$ (blue dotted curve), corresponding to the actual motion and the reference motion. The graphs in the right column of Fig. 4.2a and the columns of Fig. 4.2b represent similar meaning.

As shown in Fig. 4.2, all predicted forward motions (dashed green curve) for subjects are coincident with experimentally determined motions (solid black curve), while predicted trajectories (dashed blue curve) corresponding to the reference motion (solid red curve) are not completely coincident with the model trajectory. The error between the reference motion of the forward and inverse dynamics is caused by the theoretical, instantaneous

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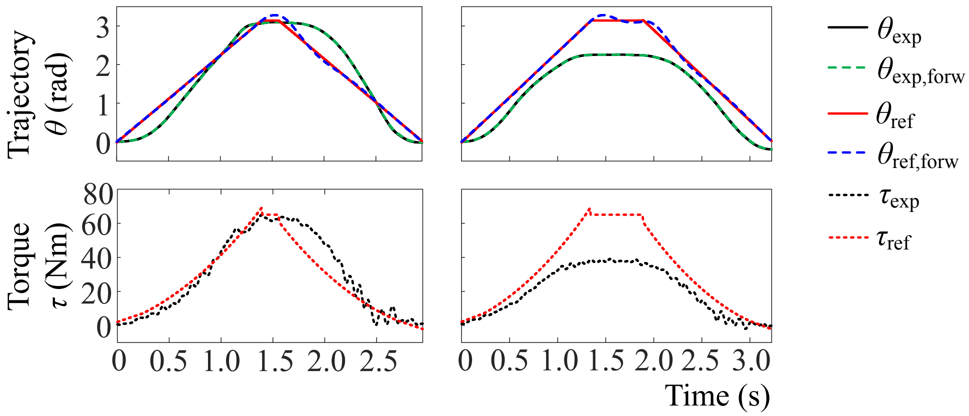
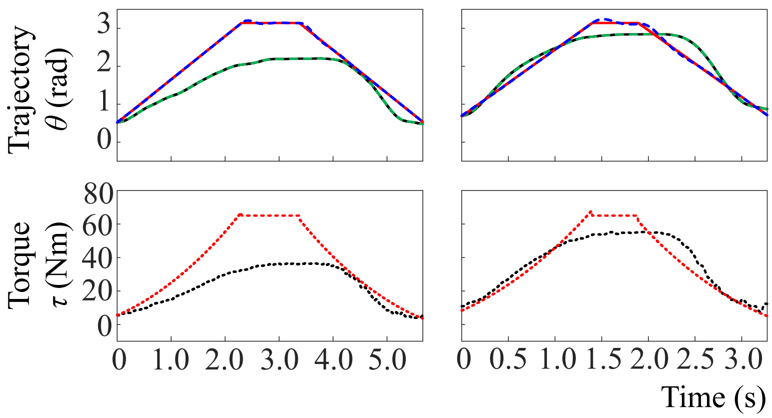


(a) Experiments for validation of dynamical model of one control's nondominant (left) and dominant (right) arm



(b) Experiments for validation of dynamical model of one patient's paretic (left) and nonparetic (right) arm

Figure 4.2: Trajectories and torques sensed in the inverse and forward dynamics of system model for one healthy control and one post-stroke patient

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change in velocity, which is not realizable by either real physical systems or simulation algorithms. Therefore we assume that this error is negligible and believe that the system model in Fig. 3.4 is capable of mimicking the dynamics of the limb during shoulder flexion. Furthermore, as shown in the bottom panel Fig. 4.2a and Fig. 4.2b, there is a difference ($\Delta\tau$, for simplicity) between τ_{exp} (dotted black curve) and τ_{ref} (dotted red curve) in all cases. However, graphically speaking, the difference in $\Delta\tau$ between the two arms of the stroke patient in Fig. 4.2b is greater than that between the two arms of the healthy control in Fig. 4.2a.

4.4 Data Processing

We measure the difference of output torque between experimental model and reference model by mass–normalized *root mean square error* (RMSE):

$$RMSE = \frac{1}{m}\sqrt{\frac{\sum_{i=1}^{i=N}(\tau_i - \hat{\tau}_i)^2}{T}} \tag{4.1}$$

where m is the mass of the limb and T is the total motion time, which may include a pause duration. τ_i and $\hat{\tau}_i$ represent torques derived from the experimental motion and reference motion, respectively [134]. N denotes the number of sampling points in the motion vector T (The Simulink environment is assigned with fixed–step solver, with a step size of 0.04/128). For each participant, the difference in RMSE between the two arms indicates the difference in their limb performance.

Considering that there were at most three possible RMSEs for each arm of the post-stroke participants (one per trial), we picked three RMSEs from the 10 trials by each arm of healthy controls. Although there were small variations in the magnitude of these 10 RMSEs, we picked the RMSEs from Trial 1, 4, and 9 of the control group, corresponding to the first, middle, and last trial of post-stroke group, in order to reduce the potential influence of order on task performance. Moreover, in terms of our hypothesis and the general rules of the UE-FMA, which is scored according to the best performance, in the later data analysis

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we will take the minimum RMSE that each individual arm demonstrated as the decisive representative performance of that arm.

Given the evident difference in the magnitude of RMSE among controls (for the dominant arm, $median = 90.5130$, $range = 164.2674$; for the non-dominant arm, $median = 78.5695$, $range = 128.4346$.), we propose a novel measurement, $w_{limb}^{participant}$, to evaluate the performance across individuals

$$w_{limb}^{control} = \frac{RMSE_{limb} - RMSE_d}{RMSE_d} \tag{4.2}$$

$$w_{limb}^{stroke} = \frac{RMSE_{limb} - RMSE_{np}}{RMSE_{np}} \tag{4.3}$$

where $w_{limb}^{control}$ (Eq. 4.2) and w_{limb}^{stroke} (Eq. 4.3) represent the measurement w for the healthy controls and the post-stroke participants, respectively. For the evaluation of controls in Eq. 4.2, the subscript *limb* denotes the relevant arm, i.e., the dominant arm (d) or the non-dominant arm (nd). Similarly, in Eq. 4.3 for the evaluation of performance by individuals post-stroke, the term *limb*, can be the paretic arm (p) or the non-paretic arm (np). The greater the magnitude of $w_{nd}^{control}$ (w_p^{stroke}), the greater difference in the motor ability between the two arms. Moreover, theoretically speaking, $w_{nd}^{control}$ (w_p^{stroke}) can be either positive or negative. A positive value indicates that the dominant (non-paretic) arm performs better than the non-dominant (paretic) arm. Conversely, a negative value indicates that the non-dominant (paretic) arm performs better than the dominant (non-paretic) arm. Therefore, we expect the magnitude of w_p^{stroke} in the post-stroke group to be larger than $w_{nd}^{control}$ of the control group, and the magnitudes of $w_{nd}^{control}$ of the control group to be close to zero.

Finally, due to the small sample size (6 controls and 5 patients) in our study [135], we conduct a nonparametric test, the *Mann-Whitney U test*, on the variable $w_{limb}^{participant}$ between the control group and the patient group, with the alternative hypothesis (H_1) that w_p^{stroke} of the patient group has a larger value than $w_{nd}^{control}$ of the control group. We also run the Mann-whitney U test across the control subjects, to check if there is a statistical difference between the dominant and non-dominant arms. Both tests are run on SPSS, with a significance level $\alpha = 0.05$. Meanwhile, although we have two ws for Patient 10, corresponding to his/her

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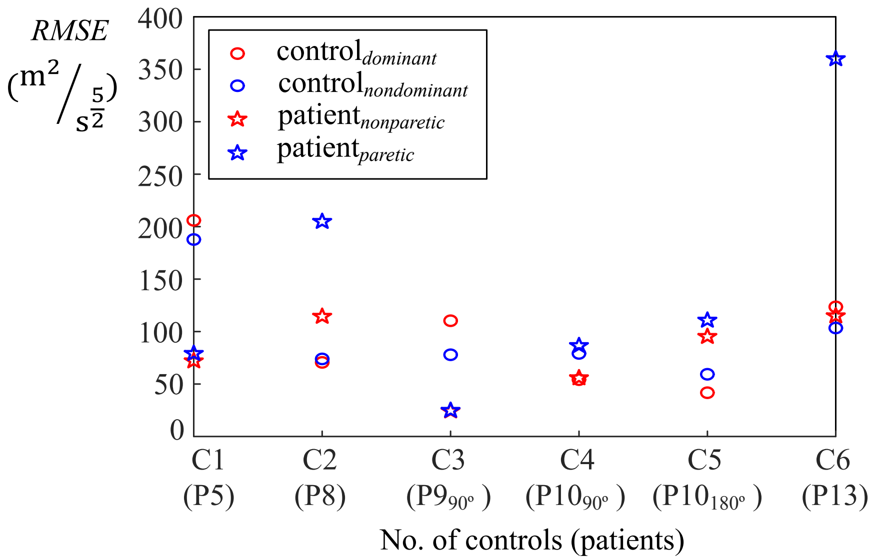

Figure 4.3: Minimum RMSE of both arms for all participants

0-90° shoulder flexion and 90-180° shoulder flexion, respectively. We will utilize the former one from the standpoint that all the motions started from home position.

4.5 Results

The minimal RMSE for all participants, that is, dominant/non-dominant arms and paretic/non-paretic arms, are plotted in Fig. 4.3. And the variables $w_{limb}^{participant}$ across individuals are plotted in Fig. 4.4.

All the samples for the Mann-Whitney U test were listed in Table. 4.1. Measurement $w_d^{control}$ for the dominant arm of controls and w_{np}^{stroke} for the non-paretic arm of patients is always 0 according to Eqs. 4.2, 4.3. The first statistical test was run between $w_d^{control}$ and $w_{nd}^{control}$, and there is no statistically significance difference ($U = 18$, $p = 1.000$) between the dominant and non-dominant arms among control subjects. The second U test was run between $w_{nd}^{control}$ and the w_p^{stroke}, and there is a statistically significant difference ($U = 5$, $p = 0.041$) between the post-stroke group and the control group.

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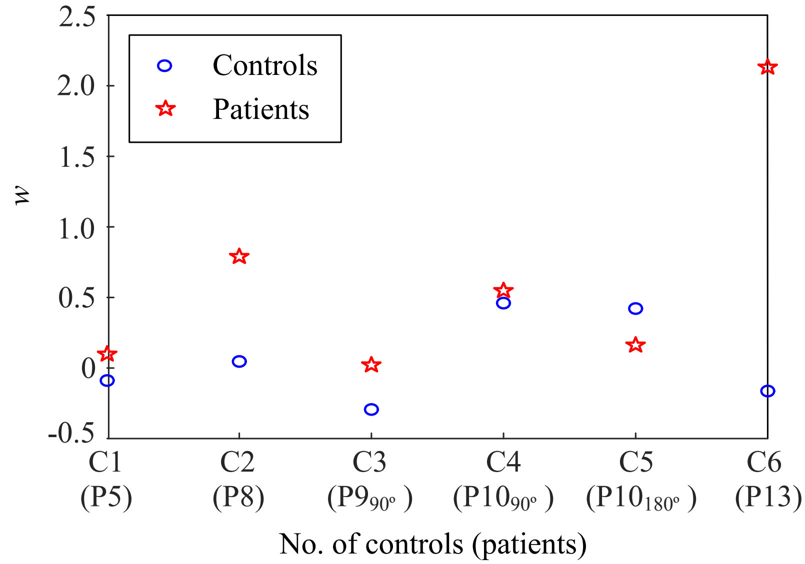

Figure 4.4: Plot of measurement $w_{limb}^{participant}$ across individuals

Table 4.1: Samples for Mann-Whitney U test

Controls			Patients		
No.	$w_{d}^{control}$	$w_{nd}^{control}$	*No.*	w_{np}^{stroke}	w_{p}^{stroke}
C1	0	-0.0885	P5	0	0.0985
C2	0	0.0465	P8	0	0.7900
C3	0	-0.2935	P9$_{90}$	0	0.0216
C4	0	0.4602	P10$_{90}$	0	0.5486
C5	0	0.4214	P13	0	2.1317
C6	0	-0.1630			

Note Patients with subscript 90 performed flexion to 90°. The others performed to 180°.

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4.6 Discussion

4.6.1 Pendulum-based Dynamical System Model

Without simultaneous, direct access to kinematic, kinetic, and human body parameters, we applied an identification approach based on a pendulum-based plant model and constructed a dynamical system model illustrated in Fig. 3.4. Using experimental kinematic data from a shoulder flexion task, this pendulum-based system model demonstrated its ability to mimic the dynamics of the limb in the shoulder flexion task, which can be understood from both qualitative and quantitative perspectives.

Qualitatively speaking, the plant model, with assignment of appropriate body parameters, $[m, l, J, k, \zeta]$ and with access to kinematic information, $[\theta, \dot{\theta}, \ddot{\theta}]$, are used to derive the time-series torque, $\tau(t)$, which then drives the plant model to produce the corresponding experimental motion. The derived torque curve $\tau(t)$ shows a similar shape to the subject's derived trajectory curve, as shown in Fig. 4.2. This originates from the assumption that muscles, with spring-like properties, play the main role in achieving movement; it also implies that joint stiffness plays the dominant role, as opposed to inertia or damping. This is consistent with existing literature [66, 69].

Quantitatively speaking, the RMSE generated by our inverse dynamical model represents the similarity between the experimental torque curve and the corresponding ideal torque curve, which is mainly originated from their similarities on symmetry of trajectories and range of motion. Because a smaller RMSE is associated with a constant-velocity shoulder flexion motion, it is reasonable to infer between-limb differences in capability using this value. From this standpoint, the pendulum-based dynamic model is able to represent the characteristic dynamical features for both control post-stroke participants. For example, RMSEs for the dominant and non-dominant arm of Control 1 were 206.03 and 187.80, respectively; these values are relatively close and suggest similar performances in both arms. Generally, control participants demonstrated this similarity in motor ability (red and blue circles, Fig. 4.3). However, there exist large differences in RMSE between the non-paretic and paretic limbs for some post-stroke participants (red and blue pentagrams in Fig. 4.3). For example, RMSEs for the non-paretic and paretic limbs of post-stroke participant 6 were

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114.96 and 360.03. The smaller value of 114.96 is associated with motion similar to the ideal constant-velocity assumption. Conversely, the larger value of 360.03 is associated with motion dissimilar to the constant-velocity assumption; it demonstrated asymmetry, increased jerk, and decreased range of motion, typical of paretic limb performance [136,137]. Therefore, we believe that this parametric dynamical system model is sensitive to the characteristic dynamics of both control and patient participants.

For indviduals post-stroke, our inverse dynamics approach generally resulted in smaller torque values for the paretic limb (Fig. 3.4). This is caused by the application of identical system parameters (m, l, J) and representations of elasticity and viscosity (Equation (3.4), (3.5)), to the paretic and non-paretic limbs. In other words, the joint angular displacement θ determines the magnitude of the elastic torque, the dominant component of the resistant torques. Therefore, the paretic limb, with comparatively smaller angular displacement, corresponds to smaller joint torque. From a neurological perspective, this may reflect various underlying physiological changes post-stroke, including loss of motor units, changes in peripheral nerve conduction, and changes in the mechanical properties of muscles [138]. Here we utilize one variable, the net joint torque, to represent the aggregate of these potential physiological changes and to indicate the potential maximal capability of the human neuromusculoskeletal system for such a shoulder abduction task. This simplified variable may be more functionally significant than the complicated analysis of individual motor units or muscles during the control process for the central nervous system, which is also suggested by Dewald and Beer [80]. In a word, it is feasible to apply this pendulum-based system model to mimic the dynamics of the UE and to identify the comparative motor ability of two limbs in a shoulder flexion task.

4.6.2 Performance of Measurement $w_{limb}^{participant}$

Now that it is feasible to tell relative motor ability between two limbs within an individual by comparing their dynamical system model–derived RMSEs (Fig. 3.4), we proposed a new variable $w_{limb}^{participant}$ to investigate the post-stroke severity across individuals. Theoretically speaking, the smaller the value of $w_{nd}^{control}$ (w_{p}^{stroke}), the more similar performance between limbs. The Mann-Whitney U tests showed that w_{p}^{stroke} of the post-stroke group is statistically

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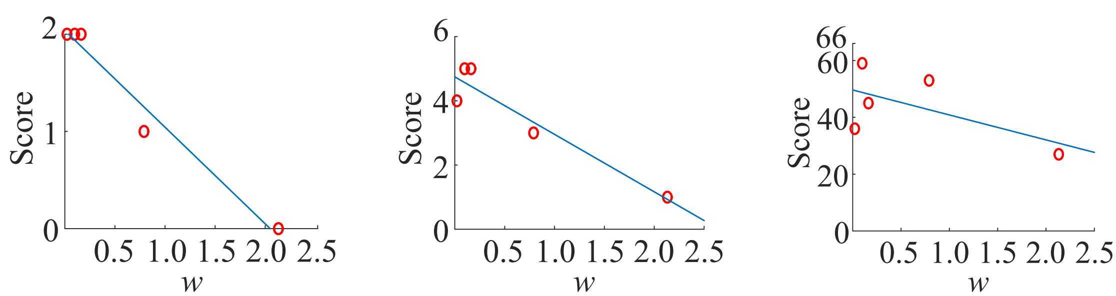
greater than $w_{nd}^{control}$ of the healthy control group ($p = 0.041$), while there was no statistical difference of $w_{limb}^{control}$ between the dominant arm and the non-dominant arm for all healthy controls ($p = 1.000$). This indicates that the measurement $w_{limb}^{participant}$ is sensitive to post-stroke severity. More specifically, the high values of w_p^{stroke} resulted from highly impaired paretic limb performance (e.g., increased jerk during motion, smaller range of motion).

Interestingly, post–stroke participants 8 and 10 showed comparatively greater values of w_p^{stroke}, 0.79 and 2.13, and their corresponding individual UE-FMA score for 90-180° shoulder flexion is 1 and 0, as shown in Fig. 4.5a. Therefore, we believe that our dynamical model is reliable to be used to identify and track UE motor impairment of individuals post-stroke. Furthermore, the quantification w_p^{stroke} can not only represent patients' performance in this specific motion of shoulder flexion, also can indicate patients' other functional abilities. Firstly, Fig. 4.5b shows a strong correlation ($\rho = -0.9497$) between w_p^{stroke} and the UE-FMA score for all out-of-synergy movements (FMA_{OoS}), which includes 0-90° shoulder abduction, 90-180° shoulder flexion, and pronation/supination of the forearm. For example, the abnormally greater values of w_p^{stroke}, 0.7900 and 2.1317, correspond to lower values of FMA_{OoS}, 3 and 1. This implication makes sense because any of these three movements requires the coordination of several muscle groups. Individuals with hemiparesis have abnormal torque patterns associated with gross co-contraction of antagonist muscle groups [80]. Therefore, it may be possible to predict impairment for all out-of-synergy movements with the availability to w_p^{stroke}. Moreover, we can infer from Fig. 4.5c that an



(a) Individual FMA score for 180° shoulder flexion

(b) FMA score for all movements out of synergy

(c) Total FMA score

Figure 4.5: Three types of UE-FMA scores (red circles) versus the factor w_p^{stroke} for all patients and the associated least-squares lines (blue lines)

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extremely large value of w_p^{stroke} may be related to a low total UE-FMA score, although the comparably low values of w_p^{stroke} are not necessarily corresponding to high total UE-FMA scores. The total UE-FMA score is a comprehensive, detailed assessments for UE motor impairment, covering hands, wrists, forearms, elbows, upper arms and shoulders and so on. However, the distribution of weakness is not uniform across the muscle groups and does not confirm to a common pattern across patients. For example, Colebatch and Gandevia found a significant difference in the severity of damage between shoulder muscles and the wrist and finger flexors [78, 80]. As a consequence, a patient with severe disability in shoulder flexion can show good functional abilities in other tasks, which leads to a higher total UE-FMA score (for example, one participant with low impairment as measured by a UE-FMA score of 53 had a value of 0.79, Fig. 4.5c.

Nevertheless, it is surprising that some patients in our study, i.e. Patient 5, 9 and 10, showed smaller w_p^{stroke}s even compared to $w_{nd}^{control}$ of the controls, as illustrated in Fig. 4.4. Fundamentally, the variable $w_{limb}^{participant}$, associated with the normal motor ability in the shoulder flexion task, falls in some range, instead of a certain value. In our study, the minimal and maximal values of $w_{nd}^{control}$ for control subjects are -0.2935 and 0.4602, respectively. Since the sample size was very small, it is highly possible that this indicates a range of $w_{limb}^{participant}$ representative of unimpaired performance. In this case, three small values of w_p^{stroke} for stroke patients, 0.10, 0.02, and 0.16, are reasonable and indicate that the paretic limbs of these three patients had comparable motor ability to their non-paretic limbs in this task [78]. Except for the individual factors, there are two possibilities that lead to more similar motor ability between the paretic and non-paretic limbs for individuals post-stroke. One possibility is the nonuniform distribution of weakness, which we have already discussed. The other possibility is that the motor ability of the non-paretic arm is also reduced by stroke, compared to healthy participants [78].

4.7 Conclusions

In our study, the pendulum-based dynamical model demonstrates the ability to quantify a proxy for the limb with only one variable, joint torque τ. For the paretic arm of individuals

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post-stroke, it is reasonable to take this ability as its maximal motor ability. The preference of non-paretic arm to paretic arm in daily life suggests that for healthy people there may be also an underlying comparison of challenge/effort required for each limb during decision-making process, i.e. limb choice. In this term, our pendulum-based plant model provides a possible, torque-based approach to investigate this dynamical decision-making process and to predict limb choice. τ can be taken as a simplified quantification of effort required by the motion for one arm. And this parametric dynamic model, which is simple but efficient, can play the role of system identification, whose significance has been emphasized in behavioral science, e.g. the energy balance model during gestational weight gain [57], and the *Craving-Sigsmked* interrelationship in the smoking behavior [58].

Moreover, with the ability to measure and quantify post-stroke severity, our dynamical system model can be applied as a convenient, reproducible approach to monitor time-varying UE motor impairment after stroke, in kinetics terms based on patients' kinematics information, which can be easily collected by wearable sensors or IMUs. And the output of model, w_p^{stroke}, is representative of stroke severity. This shows great convenience in a wide application of investigating and monitoring the post-stroke disability, compared to those previous researches [75–80]. Furthermore, this standardized approach provides a promising future for the adaptive intervention of post-stroke rehabilitation. With access to the ongoing kinematics of individuals post-stroke, the dynamical system model figures out the output w_p^{stroke}, which can be taken as the *tailoring variable* and indicate the adjusting intervention through the decision rules. Therefore, this will be a fundamental step for a powerful and cost-efficient adaptive intervention for post-stroke rehabilitation.

However, there are two potential limitations that may reduce the accuracy of our model in evaluating the motor ability across limbs and the stroke severity across individuals. The first one is the definition of the reference motion. Currently in our study the reference motion is simplified as a constant-velocity motion, which deviates from natural human behavior and may therefore result in a deviation from the exact $w_{limb}^{participant}$, which is calculated from the difference between one participant's actual motion and the naturally-optimized motion. The other weakness in our study is the small sample size. Therefore, on one hand, our future work will be focus on the optimization of the reference motion, which is important to reduce

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the variance of $w_{limb}^{participant}$ corresponding to different level of severity. On the other hand, we will try to investigate a larger population and to recognize the underlying motor impairment by quantification $w_{limb}^{participant}$ more accurately.

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Chapter 5

Construction of Markov Decision Process for Dynamic Limb Choice

Markov decision process (MDP) is a comparatively simple simulation modelling approach to understand the driving/controlling forces behind a system behavior. In this chapter, we applied the method of MDP to investigate the primary factors controlling post-stroke patients' making decisions on limb choice during physical activities. Based on the arm physical model developed in Chapter 3, we implemented the MDP model for our interested stroke patients' behavior in the environment of Matlab/Simulink.

5.1 Fundamental Components in a General MDP

Markov decision process, or MDP, is a popular mathematical approach to model the sequential decision problems. As a special case of reinforcement learning (RL), naturally speaking, MDP also stems from the idea that a learning system adapts its behavior in order to maximize something in an environment. There are five fundamental elements in an MDP model, mathematically expressed as $\mathcal{M} = (S, A, P^a_{ss'}, R^a_{ss'}, \gamma)$ [86], where

- S is the state space,
- A is the action space,
- $P^a_{ss'}$ is the transition probability from state s to state s', given taking the action a,

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- $R^a_{ss'}$ is the expected reward obtained during the transition from state s to state s' with taking the action a,
- γ is the discount factor.

Basically, an MDP models the interested system dynamics/behaviors as transitions from one state to another state. All states here have the Markov property, that is, the states compactly summarize the past and successfully retain the relevant information to predict the future. Moreover, if the state and action space are finite, we call it *finite Markov decision process* (finite MDP). We can specify a particular finite MDP with its state space S, action space A, and one-step dynamics of the environment. Meanwhile, the one-step dynamics can be mostly represented by the elements $P^a_{ss'}$ and $R^a_{ss'}$. Although we denoted these two quantities associated with the current state s, the next possible state s', and the action a simultaneously, it is possible that they are merely a function of some of these three variables. The reward R is essentially the quantification of goal(s) the learning system (also referred as agent) wants to obtain. As a result, from a mathematical perspective, in MDP the agent's goal is to maximize the total amount of reward, the accumulated rewards over the long term. For the last item of discount factor, $\gamma \in [0, 1]$, it determines the present value of future rewards. Specifically, from a mathematical perspective, the discount factor $\gamma \in [0, 1)$ ensures that the total reward remains bounded during computation.

After the specification of above-mentioned elements, to model a sequential decision problem, we also need to determine the time points t (called *decision epochs*) of making decisions, and the whole time course T (called *time horizon*) we model system behaviors. Obviously, the horizon is the set of decision epochs, that is, $T \equiv \{1, 2, 3, ..., N\}$, where N denotes the length of the time horizon. A finite N corresponds to a finite horizon problem. Both the decision epoch t and horizon T should be chosen to represent a meaningful clinical application [84].

5.2 Specification of MDP for Dynamic Limb Choice

In an environment where an individual with hemiparesis needs to perform a task with one arm, it has been suggested that there could be a wide and varied range of factors

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influencing his/her limb choice [36, 107, 139–143]. In other words, there may exist many factors simultaneously controlling (i.e., motivating and/or preventing) the paretic limb use, such as functional ability, feeling of depression or confidence, and support from family or community. To enable the long-term participation of stroke survivor in physical activities and thereby maximize the rehabilitation outcome, up to now, scholars have been spending lots of work and time to figure out potential factors influencing patients' adherence to exercise. However, due to the complexity (i.e., exercise-dependent, interrelation between factors) and diversity (i.e., personal and social context, psychological and physiological) of potential factors, there is still no universal, comprehensive understanding of these factors and their effects on adherence to exercise. In this dilemma, we go back to the nature of the dynamics described by MDP, that the agent selects actions and the environment responses in form of rewards and new states. In our modelling, definitely the agent is the human subject with hemiparesis. But the consequence (or cost/rewards) that patients obtain through performing the task from the environment could be in multiple forms. Take, for example, one common case of drinking water in daily life. The result includes that the person has consumed energy, tasted water and possibly became happy. Nevertheless, considering that we human always makes response from a physiological and/or psychological perspective, it is reasonable to assume that all potential rewards of human behavior merely in these two terms: physiological and psychological. Now based on the fundamental knowledge and assumption mentioned above, we defined the corresponding components of Markov decision process for our specific context, dynamic limb choice in individuals with hemiparesis.

5.2.1 Time Horizon T

As we briefly discussed in the Background chapter, through the approach of MDP, we are aimed to investigate and understand the underlying mechanism of the behavior that patients with hemiparesis do not use their paretic limb as initially prescribed (e.g. the learned non-use), even though they possess sufficient motor ability in their paretic limb. This nonuse evolution especially exists in the sub-acute and chronic stages of stroke rehabilitation and may worsen the eventual abnormality of motor patterns. Moreover, most recovery from impairment after stroke has been shown to occur within 6 months and currently the majority

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of outpatient rehabilitation studies track the recovery progress within 6 months [23–26, 144]. Therefore, we focus our modelling on an about-6-month-length dynamic progress and choose the time horizon $T \equiv \{1, 2, 3, ..., 200\}$. From the viewpoints of both clinical therapists and patients, one day is a good, meaningful time interval. In this case, practically the decision epoch t maps to a task in Day t, or the number of task.

5.2.2 States S and Actions A

As suggested by Sutton and Barto [86], the state is sensed by the agent in an environment, affected by actions selected and associated with the agent's goal(s). We defined Markov states according to patients' motivation in using the paretic limb. Although usually people only talk about two motivation levels [145, 146], i.e., high/low motivation or motivated/unmotivated, which were based on interviews from a qualitative perspective, the line between "motivated" and "unmotivated" is suggested not a rigid one [146]. Therefore, it is reasonable simplification to define that there are three motivation states, that is, State 1 (s_1), State 2 (s_2), and State 3 (s_3), corresponding to negative, moderate and positive motivation, respectively. More specifically, an individual in state s_2 (s_3) is more motivated to use the paretic limb than in state s_1 (s_2). Obviously, in any states there are always two possible actions, paretic-limb use and nonparetic-limb use, which we expressed as a_1 and a_2, respectively.

5.2.3 State-transition Matrix P

Given there are n states, generally each action corresponds to a n-by-n state-transition matrix P. In our MDP, there are two 3-by-3 state-transition matrices, $P(:, :, 1)$ and $P(:, :, 2)$, separately corresponding to action a_1 and a_2. Each element p_{ij} in transition matrix $P(:, :, 1)$ ($P(:, :, 2)$) represents the probability of transiting into state j from state i when taking action a_1 (a_2). And the sum of probability in one row is always equal to 1. Moreover, we assume that the action of paretic-limb use, a_1, would support the transition to a state with higher motivation, for example, the elements p_{12}, p_{23}, and p_{33} in matrix $P(:, :, 1)$ are always greater than those in matrix $P(:, :, 2)$. For the convenience of investigation in future, we express

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$P(:,:,1)$ and $P(:,:,2)$ as following,

$$P(:,:,1) = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix}, P(:,:,2) = \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{bmatrix} \tag{5.1}$$

5.2.4 Immediate Reward Function R

In Markov decision process, the expression of immediate reward R is very decisive to find out the sequential optimal decisions. The reward formulizes the goals/signals that the agent wants to achieve and maximize. As we discussed mentioned before, there may be a list of costs and/or gains for a post-stroke individual when performing a task, for example, consumed energy, pain, improvement in functional ability etc. The variation and number of these resulted rewards makes it more difficult to map patients' behavior of dynamic limb choice into MDP. However, if we consider the reward from the underlying causes, that is, patients' psychological and physiological ability, instead of those resulted costs and gains in multiple forms, we can simply describe the immediate reward as the summation of two parts,

$$r_{limb} = U_{limb}^{limbchoice} + U_{limb}^{taskperform} \tag{5.2}$$

The subscript $limb$ refers to the limb (paretic or non-paretic) patients may choose to perform the task, which exactly represents the action. The superscript $limbchoice$ and $taskperform$ indicate the reward originated from patients' psychological and physiological ability. We will provide more details on these two terms in the following.

First Component of Reward: $U_{limb}^{limbchoice}$

More specifically, the first term $U_{limb}^{limbchoice}$ is the quantified perceived benefits from using the paretic (or non-paretic) limb. This term dependents on individual knowledge about the benefit of using paretic limb, such as improving functional ability and overall health status, and reducing risk [35, 36, 106, 142, 147]. From the standpoint of stroke recovery, we thereby

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explicitly define this term for the conditions of paretic- and nonparetic-limb use as

$$U_{limb}^{limbchoice} = \begin{cases} c & limb = p \\ 0 & limb = np \end{cases} \tag{5.3}$$

where the symbols p and np have the same meaning we mentioned in Chapter 4. And c is a nonzero value, which is usually positive. The more detailed setting will be discussed in the following sections. Moreover, $U_{limb}^{limbchoice}$, an identification of perceived benefits, can also be regarded as essentially from a psychological perspective.

Moreover, the perceived benefits $U_{p}^{limchoice}$ should be different when patients are in different states. We expect that paretic-limb choise have a greater positive significance for a person in a state of higher motivation. Therefore, we additionally apply three weight factors, α_1, α_2 and α_3, to represent the relative significance of perceived benefits $U_{p}^{limchoice}$ for state s_1, s_2 and s_3, respectively. For the simplification of simulation modelling, generally we set $\alpha_2 \equiv 1$ as a reference, $\alpha_1 < 1$, and $\alpha_3 > 1$. Notably, since $U_{np}^{limchoice} \equiv 0$, we did not set any weight factor for it.

Second Component of Reward: $U_{limb}^{taskperform}$

Comparatively, the second term $U_{limb}^{taskperform}$ is originally determined by the physiological ability in patient's paretic (or non-paretic) limb. The impaired limb in individuals with hemiparesis will exhibit functional disability and motor disability compared to the unimpaired limb. As a consequence, individuals may suffer from weakness of arm, decreased range of motion, depression, fatigue, and even low confidence in the future, when performing a task with the paretic arm. In one work, although the second component of reward is determined by patients' physiological ability, using the paretic limb will have physiological and psychological effects [35, 36, 108]. As we mentioned, we will represent both effects in term of their determinant, the physiological ability. In Chapter 3 and 4, we developed a dynamical model for human upper limb and confirmed it ability to mimic upper-extremity dynamics. We therefore here construct the reward component $U_{limb}^{taskperform}$ for paretic and non-paretic limb using our proposed arm physical model. Moreover, in terms of mechanical property, people observed that the impaired limb was associated with increased stiffness,

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compared to the non-impaired limb [148–150]. However, most of these studies focused on a fixed limb position and posture. As a result, currently we simply represent this increased stiffness k' as

$$k' = c_{impair} \cdot k \tag{5.4}$$

where k is the joint stiffness expressed by Equation 3.4. The parameter c ($c \geq 1.0$) indicates the increased level of stiffness, or the stroke severity, roughly speaking. A greater value of c corresponds to the case of more severe in motor impairment. Obviously, $c = 1.0$ maps to the non-impaired case. Now with the combination of the arm plant model (Fig. 3.4) and the expression of increased stiffness (Equation 5.4), we can construct a forward kinematic model to compare the perform between the paretic and non-paretic limb for any individual. Furthermore, considering that the gains and costs represented by $U_{limb}^{taskperform}$ are not merely some evaluation at a time point, but physiological and psychological effects over a time course, we therefore compute $U_{limb}^{taskperform}$ based on the integration of angular displacements over the motion time t, which can be expressed as following,

$$U_{limb}^{taskperform} = \begin{cases} \frac{\int_0^t \theta_p dt'}{\int_0^t \theta_{np} dt'} & limb = p \\ 1 & limb = np \end{cases} \tag{5.5}$$

where θ_p and θ_{np} denote the time-series angular displacement curve derived by the paretic arm model and non-paretic arm model, respectively. Empirically speaking, there is usually a goal/target (e.g. position) pre-designed for participants, which is not satisfied by our modelling. Practically speaking, when making the decision of which limb to use without any specific requirement, we mostly compare the capability between our two arms unconsciously internally, not externally. Therefore, we assign a ideal reference value of 1 to the non-paretic limb, which possess at least as good functional ability as paretic limb. Then through the ratio of time integration of angular displacement between paretic and non-paretic limb, we obtain $U_p^{taskperform}$, exactly equal to the ratio.

We implemented the model for calculation of $U_{limb}^{taskperform}$ in Matlab/Simulink as shown in Fig. 5.1. In our previous experiments of shoulder flexion, the maximum motion time from home position to goal position is about 3.2s by one post-stroke patient with the paretic limb.

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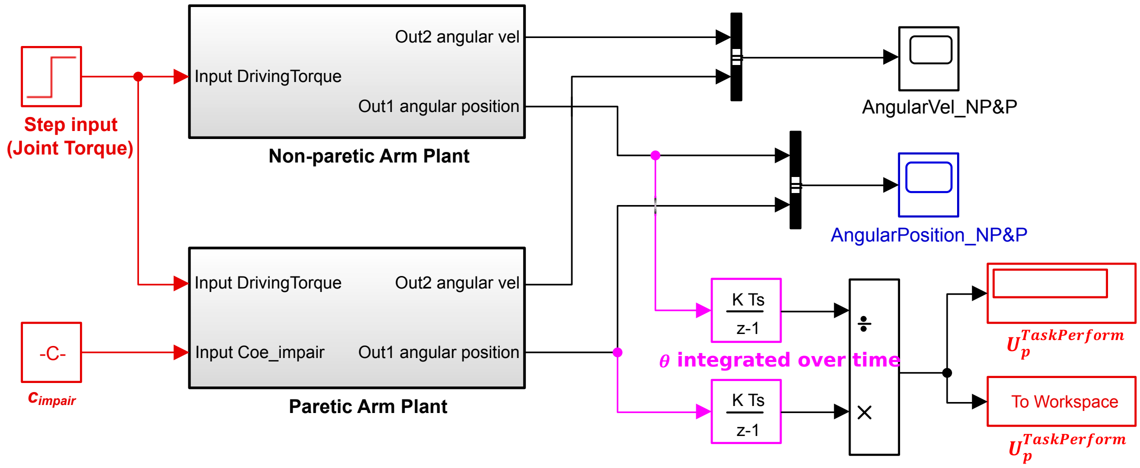
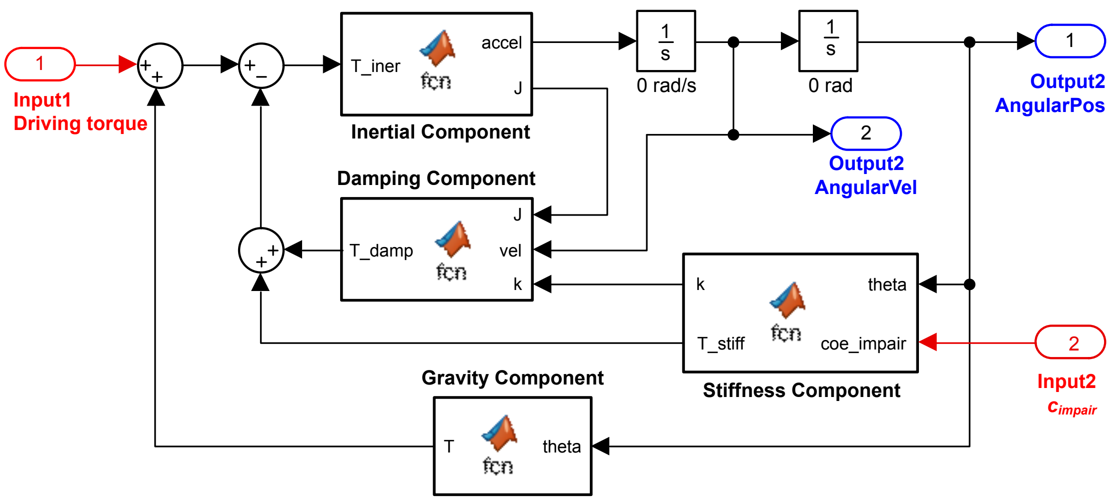


(a) The overall model to compute $U_p^{taskpeform}$



(b) The plant model of paretic arm

Figure 5.1: The model to calculate the reward compoment $U_p^{taskperform}$ in Matlab/Simulink

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We hereby set the time course for one task is 4s. Moreover, as we presented previously, we compare the physiological ability between two arms of one person based on the upper-extremity physical model developed in Chapter 3, which works as a role of a plant system, that is, the subsystem of "Non-paretic Arm Plant" and "Paretic Arm Plant" in Fig. 5.1a). For the convenience of model construction and simulation, this time we built the arm model in Matlab/Simulink (as shown in Fig 5.1b), instead of Matlab/SimScape. Furthermore, for simplification, we set the driving torque as a unit step function, to evaluate the performance of patients' two arms. Fig. 5.2 showed the performance curves, the angular displacement driven by step input, in three situations where the motor impairment $c_{impair} = 1.2$ (left column), $c_{impair} = 1.5$ (middle column), and 2.0 (right column). And the associated gains/rewards from performing task by paretic limb, $U_p^{taskperform}$, is 0.9039, 0.7901 and 0.6530, respectively.

Up to now, we have discussed all the components in the immediate rewards, we can formulize it as

$$r_{p,i} = \alpha_i U_p^{limbchoice} + U_p^{taskperform} \tag{5.6}$$

$$r_{np} = U_{np}^{limbchoice} + U_{np}^{taskperform} \tag{5.7}$$

where in Equation 5.6, $i = 1, 2, 3$, corresponds to State 1, State 2, and State 3, respectively. Meanwhile, the first term represents patients' perceived benefits on a psychological perspective, and the second term captures all the potential resulted psychological effects such as self-efficacy, confidence, and depression, and physiological effects such as decreased range of motion and pain.

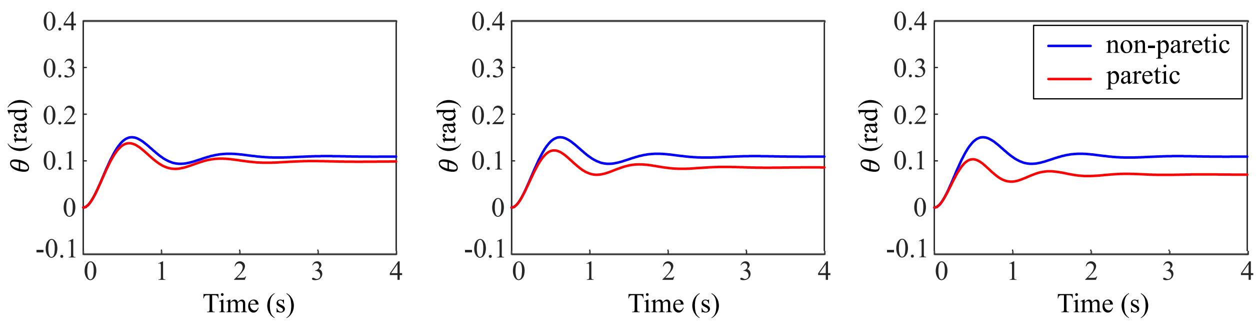

Figure 5.2: Angular displacement curves $\theta(t)$ when computing $U_p^{limbchoice}$ under the condition of $c_{impair} = 1.2$ (left), $c_{impair} = 1.5$ (middle), and $c_{impair} = 2.0$ (right)

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Influence of Post-stroke Progression on $U_p^{taskperform}$

During the rehabilitation process, definitely the disease progression is dynamic, that is, patients' motor impairment is varying, which is a primary component of the immediate reward R_p (Equation 5.6 and 5.10) that patients obtain in one task. As we discussed previously, this term, $U_p^{taskperform}$, is decisive for action selection. Therefore, the feature of varying motor impairment is required to be considered in our MDP modeling in order to to accurately evaluate patients' behavior of limb choice. Unfortunately, currently there is few model quantitatively describing the dynamics of motor impairment in a rehabilitation process. Nevertheless, previous studies suggested some rough curves for motor recovery that most gains happened in the first weeks/months, and marginal gains later [75, 151–155]. Therefore, we assume that a patient' motor recovery curve (c_{impair}) versus time t can be described as a population (logistic) growth model in Equation 5.8,

$$c_{impair}(t) = 1 + e^{-r*(t-t_0)} \tag{5.8}$$

For motor recovery curve in patients with hemiparesis, the parameter r determines how fast patients get recovered from an initial impairment, $c_{impair,0}$. Obviously, a larger r is associated with a faster motor recovery. We assigned values to r based on the fact that most recovery happened in the first month and that patients with a milder stroke severity recovered faster compared to those with a more severe one [75, 151–155]. Another variable, t_0, here is determined by

$$t_0 = \frac{\log(c_{impair,0} - 1)}{r} \tag{5.9}$$

Therefore, t_0 is actually a dependent parameter that can be easily computed given c_{impair} and r. Combining Equation 5.8 and 5.9, it can be seen that at $t = 0$ the motor impairment is $c_{impair,0}$ (the very beginning of recovery) and that the possibly minimum motor impairment is 1 (completely recovered). In our experiments, we considered the cases with an initial motor impairment 1.2, 1.5 and 2.0, and assigned their r to be 0.07, 0.05, and 0.02, respectively. The simulated motor recovery curves in these cases are shown in Fig. 5.3. The model in Equation 5.8 is obviously a very ideal simplification for stroke progression. However,

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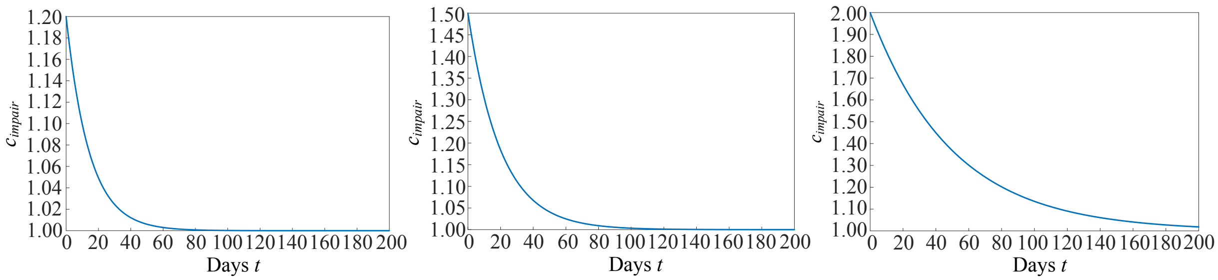

(a) $c_{impair,0} = 1.2$, $r = 0.07$ **(b)** $c_{impair,0} = 1.5$, $r = 0.05$ **(c)** $c_{impair,0} = 2.0$, $r = 0.02$

Figure 5.3: Three simulated motor recovery curves based on population growth model

considering the primary role of this dynamic motor recovery curve in MDP modelling, the simplified motor recovery curve is still constructive for our systematical investigation of factors influencing stroke patients' adherence to paretic-limb use.

In general, in each decision epoch, patients make decision on limb choice, for example, Action 1 of paretic limb choice (or Action 2 of non-paretic limb choice), and consequently obtain an immediate reward R_p (or R_{np}), which can be separately expressed by Equation 5.10, in which the i^{th} row corresponds to State i, $i = [1, 2, 3]$. Each element in R_p and R_{np} is calculated based on the patients' psychological and physiological ability, that is, the perceived benefits from limb use for stroke rehabilitation ($U_{limb}^{limbchoice}$) and the varying motor impairment ($c_{impair}(t)$). As a results, the immediate reward functions R_p and R_{np} are influenced by three variables, $U_{limb}^{limbchoice}$, $U_{limb}^{taskperform}$, and the weight vector $[\alpha_1; \alpha_2; \alpha_3]$.

$$R_p = \begin{bmatrix} r_{p,1} \\ r_{p,2} \\ r_{p,3} \end{bmatrix}, R_{np} = \begin{bmatrix} r_{np} \\ r_{np} \\ r_{np} \end{bmatrix} \tag{5.10}$$

5.2.5 Discount Factor γ

As we mentioned at the beginning, in MDP, the discount factor γ is in the range of $[0, 1]$ and determines the present value of future rewards. With one of the extreme values, $\gamma = 0$, the agent is "myopic" in that it only concerns about the immediate reward. In our specific case, this indicates that patients totally do not care about the outcomes of stroke recovery in future, instead, only the reward obtained in current task, which is not supportive to stroke

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recovery. Comparatively, with a value γ more close to 1, the agent is more "far-sighted" because of taking future rewards into consideration more strongly in making decisions. We can expect that the greater γ is, the better the rehabilitation results becomes.

5.2.6 Diagram of MDP for Dynamic Limb Choice

Based on the fundamental elements we have discussed for our specific issue, we constructed the model of Markov Decision Process (MDP), to understand the phenomenon that individuals post-stroke suppressed their paretic-limb use in daily life. The diagram of MDP is shown in Fig. 5.4. In our Markov model, there are three states (the light blue, large circle), representing how motivated/desirable an individual are to use the paretic limb. Individuals can transit from one state to any other state, although the probability of transition to a non-neighboring state is very tiny. In one decision epoch, no matter which state an individual is in, he/she can make decisions of paretic (the red, solid node in Fig. 5.4) or non-paretic (the blue, solid node in Fig. 5.4) limb use, with some expected immediate reward and transition probability (the grey number along the arrow).

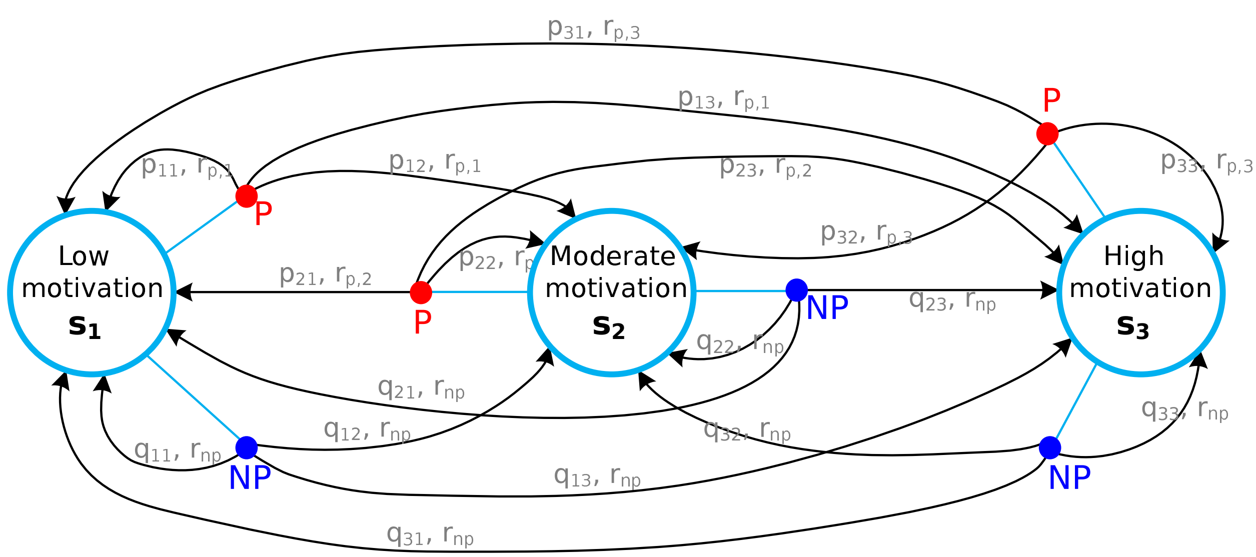

Figure 5.4: Diagram of Markov Decision Process (MDP) for stroke patients making decisions between paretic-limb use and nonparetic-limb use in daily life

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5.3 Algorithm to solve MDP

After constructing all the information in Fig. 5.4, i.e., the state space$S$, the action space A, the state-transition matrix P, and the reward function R, is known, we need to solve the Markov decision process and find out the optimal policy, that is, the set of decisions in time horizon T so that the agent (stroke patients) can maximize the accumulated reward over the long term. People have proposed a list of methods to solve MDP, for example, policy iteration, value iteration, and Q-learning. Although that people choose one of these algorithms according to the specific context (e.g., uncertainty of environment, and uncertainty of rewards), most application is based on one principle: in a given state, choose the action that will lead to the maximum accumulated reward.

There are two more important definitions for solving MDP, the *state-value function* $V^{\pi}(s)$ and the *action-value function* $Q^{\pi}(s,a)$, where π is a policy, a set of decisions. The function $V^{\pi}(s)$ (or $Q^{\pi}(s,a)$) quantitatively evaluates how good it is for the agent to be in one state s (or how good it is for the agent to take action a in a given state s), by computing the expected accumulated future reward. The detailed calculation is shown in the following Equation 5.11 (or Equation 5.12).

$$V^{\pi}(s) = \sum_{a} \pi(s,a) \sum_{s'} P^{a}_{ss'}[R^{a}_{ss'} + \gamma V^{\pi}(s')] \tag{5.11}$$

$$Q^{\pi}(s,a) = R^{a}_{s} + \gamma \sum_{s'} P^{a}_{ss'} V^{\pi}(s') \tag{5.12}$$

In Equation. 5.11, a represents all the actions from the action space A, and s' represents the next state, accordingly. The rest variables, $P^{a}_{ss'}$ and $R^{a}_{ss'}$, have the same meaning we explained in Section 5.1. There is a small difference in Equation 5.12 of action-value function, where a merely represents the interested action. And R^{a}_{s} denotes the expected immediate reward taken action a in state s. Note that in modelling the value of terminal state is always assumed to be zero [86]. Furthermore, among all policies, there is at least one policy that is better than or equal to all the other policies, which is named *optimal policy* (denoted π^{*}), and associated with *optimal value function* (denoted V^{*}) and *optimal action-value function*

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(denoted Q^*). Mathematically, this can be expressed as

$$V^*(s) = \max_{\pi} V^{\pi}(s) \tag{5.13}$$

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) \tag{5.14}$$

Note that both state-value function $V^*(s)$ and action-value function $Q^*(s,a)$ have already taken into account the future rewards. As a result, for any state s, given $Q^*(s,a)$ we can simply find out the optimal action(s) by choosing the action(s) associated with the maximum $Q^*(s,a)$.

One of the greatest challenges in our MDP is that the immediate reward is changing due to the disease progression, which has been assumed to be constant in most other studies. On the other hand, the action values in our model are without uncertainty, which ensures us that we could compute the optimal action in each decision epoch by simply choosing the one with highest value. Therefore, we applied the *backward induction algorithm* [156] to solve our MDP and find the optimal policy. The principle idea underlying backward induction algorithm is shown in Algorithm 1.

Algorithm 1 The functional backward induction algorithm

Initialize $V_0^* \leftarrow [0;0;0]; \tau \leftarrow 0$
repeat
  $\tau \leftarrow \tau + 1$
  Update r_s^a
  for all $s \in S$ **do**
    for all $a \in A$ **do**
      $Q_\tau^*(s,a) \leftarrow r_s^a + \gamma \sum_{s'} p_{ss'}^a V_{\tau-1}^*(s')$
    end for
    $\pi_\tau^*(s) \leftarrow \arg\max_a Q_\tau(s,a)$
    $V_\tau^*(s) \leftarrow \max_{a \in A} Q_\tau(s,a)$
  end for
until $\tau = 200$

Here, the variable τ denotes the number of backward iteration, that is, τ^{th}-to-last step (or epoch). As we mentioned before, the length of horizon in our finite MDP is $N = 200$, therefore the backward induction will repeat for 200 times. $\pi_\tau^*(s)$ and $V_\tau^*(s)$ represent the

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optimal policy and the optimal state value in the τ^{th}-to-last epoch. In each iteration, we firstly updated the reward function r_s^a based on patients' dynamic motor impairment, c_{impair}. Then for each of the three states, we calculated and compare the two action-value function, $Q_\tau^*(s, a_1)$ and $Q_\tau^*(s, a_2)$. The greater one would be taken as the state value $V_\tau^*(s)$, and the associated action is chosen as the optimal action.

5.4 Construction of MDP in Matlab/Simulink

Combing our specific elements of Markov decision process and the functional backward induction algorithm mentioned above, we implemented the MDP and the algorithm in Matlab/Simulink, to investigate the factor(s) that drive/control patients' limb choice physical activity during post-stroke rehabilitation process. The overall algorithm (Algorithm 2) is shown as following. Meanwhile, we updated the reward composition from performing the

Algorithm 2 Implementing and solving Markov decision process

Initialize $P(:,:,1); P(:,:,2)$
Initialize $c_{impair,0}$
Initialize $U_p^{limbchoice}$
Initialize $[\alpha_1; \alpha_2; \alpha_3]$;
Initialize γ
Initialize $V_0^* \leftarrow [0; 0; 0]; \tau \leftarrow 0$
repeat
    $\tau \leftarrow \tau + 1$
    Update r_s^a
    for all $s \in S$ **do**
        for all $a \in A$ **do**
            $Q_\tau^*(s, a) \leftarrow r_s^a + \gamma \sum_{s'} p_{ss'}^a V_{\tau-1}^*(s')$
        end for
        $\pi_\tau^*(s) \leftarrow \arg\max_a Q_\tau(s, a)$
        $V_\tau^*(s) \leftarrow \max_{a \in A} Q_\tau(s, a)$
    end for
until $\tau = 200$

task, $U_{limb}^{taskperform}$, using the arm physical model developed in Chapter 3 in Simulink. In each iteration τ, we applied this updated $U_{limb}^{taskperform}$ to compute the new immediate reward R

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and further two action-value functions $Q_\tau(s, a_1)$ and $Q_\tau(s, a_2)$, and accordingly make the optimal decision for each state.

Fig. 5.5 showed one simulation result. The three subfigures from top to bottom correspond to the case of an individual being in State 1 (s_1, negative motivation), State 2 (s_2, moderate motivation), and State 3 (s_3, positive motivation), respectively. In each subfigure, x-axis represents the number of decision epoch, i.e., the number of task. As we discussed before, the length of our horizon is $N = 200$, which is therefore the maximal x coordinate. The y-axis represents the optimal action an individual will make in a task. The value 1 and 2 denote Action 1 (a_1, paretic-limb use) and Action 2 (a_2, nonparetic-limb use), separately.

Furthermore, we propose one novel concepts, *dangerous epoch*. Think about the motor recovery curve we assumed earlier, if an individual post-stroke follow the exercise very well, at the end of recovery progress his/her motor ability would be improved to such a good level that the immediate reward in the paretic-limb use is greater than the immediate reward in the nonparetic-limb use. Thus we expect that individuals at the end would make the paretic limb choice, which is exactly what Fig. 5.5 shows (For example, the optimal action from the epoch 180 to 200 (denoted $e(108 : 200)$) is always paretic limb use). However, during the backward induction iteration, the optimal action for the individual in epoch t could be *firstly* derived to be Action 2, which means that the accumulated reward for epochs $e(t : 200)$ in paretic-limb use is no longer greater than (strictly speaking, less than) in nonparetic limb use. Due to the monotonically increasing reward in paretic-limb use (that is, a summation of a constant $U_p^{limbchoice}$ and monotonically increasing $U_p^{taskperform}$), once the optimal action is shown to be Action 2 in some epoch t, the action-value function $Q_i(s, a_1)$ in any epoch i, $i = \{1, 2, ..., t-1\}$ for paretic-limb use will be always less than that for nonparetic-limb use $Q_i(s, a_2)$, and therefore the optimal action will always be the nonparetic-limb use, a_2. In other words, in this condition, it will be too challenging for an individual to adhere to the exercise program (or practice the paretic limb) during the epochs $e(1 : t-1)$, which is dangerous for a better rehabilitation. Therefore, we define the epoch t as the dangerous epoch, which is always associated a dangerous period $e(1 : t-1)$ (at least under our current assumptions), as marked in Fig. 5.5. Definitely, a result without dangerous epoch indicates

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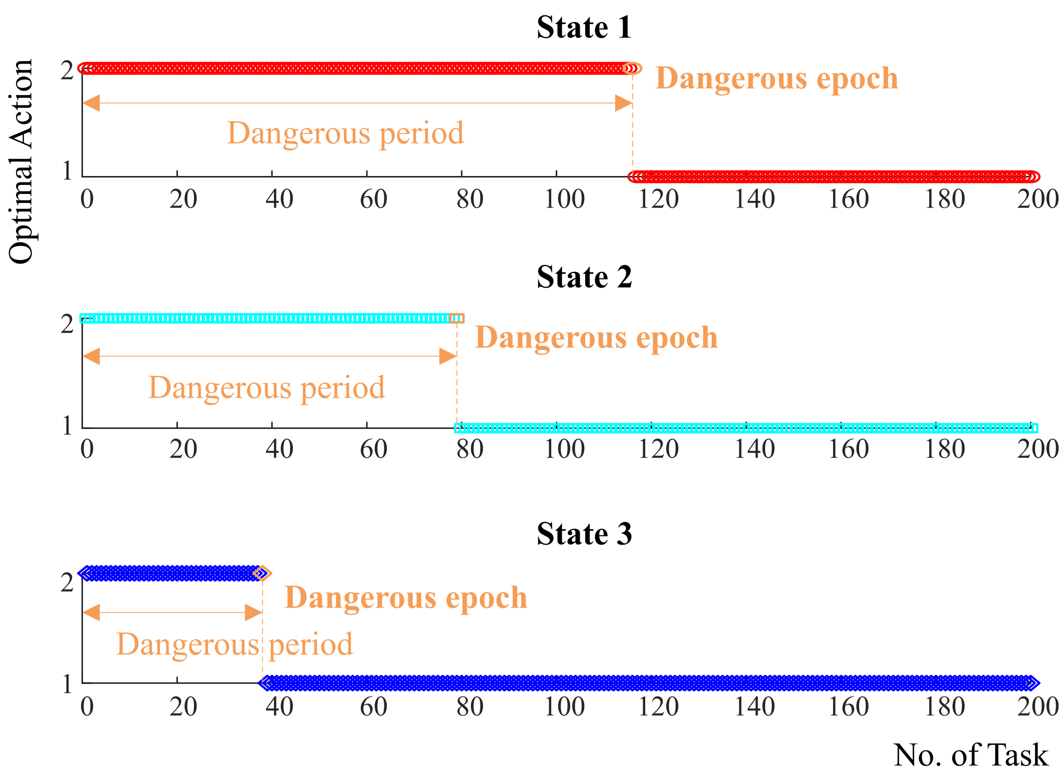

Figure 5.5: An example of simulation results by our Markov Decision Process (MDP) model

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that driven by the reward/goal, an individual can perfectly follow the instruction and always practice the paretic limb.

In later chapters, we will express and discuss our results in terms of dangerous epoch, e_d, and dangerous period, P_d. We hypothesize that an individual with a more severe motor impairment initially, and/or lower perceived benefits of paretic-limb use, and/or less motivated in paretic-limb use, would have greater difficulty in using the paretic limb in physical activity as prescribed, that is, this individual would have a greater magnitude of dangerous epoch e_d and dangerous period P_d.

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Chapter 6

Markov Decision Process Modelling for Dynamical Limb Choice

In Chapter 5, we implemented a model of Markov decision process (MDP) in Matlab/Simulink, for the phenomenon that chronic stroke patients suppress the paretic limb use during their physical activities. In this chapter, we firstly validated our MDP model through adjusting its parameters and analyzing the consequent behaviors of our model. It was shown that our MDP model is capable of quantitatively describing the phenomenon that patients chronic stroke cannot adhere to their paretic limb use as prescribed in daily life and indicating how the potential controlling factors (e.g., transition probability P, perceived benefits $U_p^{limbchoice}$ and reward from performing task $U_{limb}^{taskpeform}$) influence patients' decisions. Furthermore, we conducted some intervention experiments and accordingly provided some suggests for the cost-effective adaptive intervention for stroke rehabilitation.

6.1 Experiment I: Influence of Variables on Dynamic Limb Choice

In this section, we changed the magnitude of those primary parameters we specified in our MDP model and evaluated the consequent effects on the patients' behavior of dynamic limbc

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choice (i.e., the dangerous epoch e_d and dangerous period P_d), aimed to validate the MDP model we developed.

6.1.1 Experimental Design

Considering the system behaviors we are trying to investigate, that is, patients cannot adhere to using the paretic limb as prescribed during their rehabilitation process, definitely there is a time-varying comparative advantage (or disadvantage) in reward from the paretic limb use over the non-paretic limb use, in terms of MDP. As a results, we need to follow some principle when changing the parameters of MDP, in order to make it more representative of real world case. Generally, it is required that at least one element of the immediate reward R_p is smaller than R_{np} in Equation 5.10 at the very beginning of stroke rehabilitation. Otherwise, even in the very beginning, the most difficult rehabilitation stage for patient, there is no challenge for them to perfectly follow the instruction of practicing their paretic limb. Differently, at the very end of rehabilitation, we expect that at least one element of the immediate reward R_p is greater than R_{np}. Otherwise, in MDP modelling it would be always impossible for patients to use their paretic limb, even they do consider the benefits of exercise on stroke recovery and the long-term accumulated rewards. Furthermore, since that the experience of paretic-limb (i.e., experiences of mastery) use can encourage patients to persist in their paretic-limb use next time [109], we expect that the probability of transition into a higher-motivation state (i.e., p_{12}, p_{23} and p_{33}) is higher with the action of paretic-limb use than nonparetic-limb use. These will guide our design of parameters in our model validation.

There are five fundamental elements in our MDP model: state space S, action space A, state-transition matrix P, immediate reward function R, and discount factor γ. Obviously, all the latter three parameters have an influence on the optimal decisions during modelling. Therefore, we planned to change the values of P, R, and γ. Meanwhile, variables P and γ are in straightforward form, merely some numerical numbers. Comparatively, the immediate reward R is a complex function of reward from perceived benefits $U_{limb}^{limbchoice}$, reward from task performance $U_{limb}^{taskperform}$, and weight vector $[\alpha_1; \alpha_2; \alpha_3]$ (for detailed expression, please refer to the Subsection 5.2.4). In summary, we will investigate the influence of variation in five parameters: P, $U_{limb}^{limbchoice}$, $c_{impair,0}$, $[\alpha_1; \alpha_2; \alpha_3]$ and γ.

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Change in State-Transition Matrix P

The state-transition matrix P indicates the tendency of an individual keeping and changing how much he/she is motivated to use the paretic limb. Roughly speaking, there are three representative cases in real world,

1. no matter which state people are currently in, they transit to another state (or the current state) totally randomly (denoted *random type*);

2. no matter which state people are currently in, they always tend to transit to state s_i (denoted *converging type*);

3. no matter which state people are currently in, they always tend to stay in the current state (denoted *stabilized type*).

Now we map these three types into different state transition probabilities.

For the random type, we have the state-transition matrix as Equation 6.1. All the elements here being $\frac{1}{3}$, means that for all states, the individual can transit to any other state (including the current state) with the equal probability, that is, totally randomly.

$$P(:,:,1) = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}, P(:,:,2) = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \tag{6.1}$$

For the converging type, there could be three cases: the individual always tends to transit into State 1, 2, or 3. Correspondingly, we designed three pairs of transition matrices, as shown in Equation 6.2, 6.3, 6.4.

$$P(:,:,1) = \begin{bmatrix} 0.80 & 0.15 & 0.05 \\ 0.75 & 0.20 & 0.05 \\ 0.70 & 0.20 & 0.10 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.10 & 0.00 \\ 0.85 & 0.10 & 0.05 \\ 0.80 & 0.15 & 0.05 \end{bmatrix} \tag{6.2}$$

$$P(:,:,1) = \begin{bmatrix} 0.08 & 0.80 & 0.12 \\ 0.10 & 0.75 & 0.15 \\ 0.10 & 0.70 & 0.20 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.09 & 0.90 & 0.01 \\ 0.10 & 0.85 & 0.05 \\ 0.15 & 0.80 & 0.05 \end{bmatrix} \tag{6.3}$$

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$$P(:,:,1) = \begin{bmatrix} 0.05 & 0.15 & 0.80 \\ 0.05 & 0.10 & 0.85 \\ 0.01 & 0.09 & 0.90 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.10 & 0.20 & 0.70 \\ 0.10 & 0.15 & 0.75 \\ 0.05 & 0.15 & 0.80 \end{bmatrix} \tag{6.4}$$

Of course, these three pairs of transition matrices are only three possible settings. They could be assigned with other values. Here we are mainly aimed to investigate the effects of preference to s_1, s_2, or s_3 on optimal policy with these three examples.

For the stabilized type, we also tried three combinations considering different level of stabilized type. They are shown in Equations 6.5, 6.6 and 6.7, corresponding to highly, moderately and lowly possible to stay in current states, respectively.

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix} \tag{6.5}$$

$$P(:,:,1) = \begin{bmatrix} 0.45 & 0.50 & 0.05 \\ 0.20 & 0.50 & 0.30 \\ 0.05 & 0.40 & 0.55 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.55 & 0.40 & 0.05 \\ 0.30 & 0.50 & 0.20 \\ 0.05 & 0.50 & 0.45 \end{bmatrix} \tag{6.6}$$

$$P(:,:,1) = \begin{bmatrix} 0.15 & 0.60 & 0.25 \\ 0.35 & 0.20 & 0.45 \\ 0.20 & 0.55 & 0.25 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.30 & 0.50 & 0.20 \\ 0.45 & 0.20 & 0.35 \\ 0.25 & 0.60 & 0.15 \end{bmatrix} \tag{6.7}$$

Change in Initial Impairment $c_{impair,0}$

The variable of $c_{impair,0}$ is originated from that this will greatly influence the motor recovery curve and thus the reward from performing the task $U_{limb}^{taskperform}$. Strictly speaking, the motor recovery curve is determined by the initial motor impairment $c_{impair,0}$ and the slope r. Considering that it is not a good idea to introduce a lot of variables in the current investigation stage and that the primary goal here is the qualitative influence of $c_{impair,0}$, we will only study on three motor recovery curves here, that is, $[c_{impair,0}, r] = [1.2, 0.07]$, $[1.5, 0.05]$, and $[2.0, 0.02]$.

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Change in Reward From Perceived Benefits $U_{limb}^{limbchoice}$

Combing the results of some empirical experiments and the standpoint of the principles we presented in the beginning of this subsection, we will investigate the influence of variation in the perceived benefits on optimal policy with the following set of $U_{limb}^{limbchoice}$,

$$U_{limb}^{limbchoice} = \{0, 0.02, 0.04, 0.06, 0.08, 0.10, 0.12, 0.14, 0.16, 0.20, 0.25, 0.30, 0.40\} \tag{6.8}$$

Notably, when $U_{limb}^{limbchoice}$ is greater than 0.40, the competing between the paretic and non-paretic limb is very weak or disappears, which means that the agent would always choose the paretic-limb use as the optimal decision during the whole horizon. Therefore we stopped our simulation range at 4.0.

Change in Weight Vector $[\alpha_1; \alpha_2; \alpha_3]$

As we discussed before, for simplification, we set $\alpha_2 \equiv 1.0$. And the paretic-limb use is more valuable for an individual in a higher-motivation state than in a lower-motivation state. Therefore, in most cases of our simulation $\alpha_3 > 1.0 > \alpha_1$. The specific designs for the experiment of weight factor is listed in Table 6.1.

Change in Discount Factor γ

Based on the details we mention above, the value of γ indicates how much an individual takes the future rewards into consideration. We conducted the experiments with the following γs

Table 6.1: Pairs of $[\alpha_1, \alpha_3]$ for experiments of influence of weight vector

α_1 \ α_3	1.0	1.3	1.5	1.8	2.0	2.3	2.5
1.0							
0.8							
0.5							
0.3							
0.1							

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Table 6.2: Results of modelling the influence by change of state-transition matrix P

Type	Case	Dangerous epochs e_d ($[s_1; s_2; s_3]$)
random	random	$[116; 79; 38]$
coverging	into s_1	$[106; 78; 38]$
	into s_2	$[105; 73; 38]$
	into s_3	$[104; 73; 38]$
stabilized	highly	$[85; 61; 37]$
	moderately	$[106; 71; 38]$
	lowly	$[104; 74; 38]$

to investigate the optimal policy for a more "myopic" or "far-sighted" individual.

$$\gamma = \{0.0001, 0.30, 0.50, 0.70, 0.80, 0.85, 0.90, 0.93, 0.95, 0.98, 1.0\}$$

6.1.2 Simulation and Results

Based on the design in the five parameters (i.e., state-transition matrix P, initial motor impairment $c_{impair,0}$, perceived benefits $U_p^{limbchoice}$, weight factor $[\alpha_1; \alpha_2; \alpha_3]$, and discount factor γ), we conducted the simulation modelling and investigated their consequent effects.

Results I: Changing State-Transition Matrix P

In this session, the variable is the state-transition matrix P. We assigned the same values to other parameters, that is,

$$c_{impair,0} = 2.0; U_p^{limbchoice} = 0.1; [\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]; \gamma = 0.95$$

The simulation results were recorded in Table 6.2.

Results II: Changing Initial Motor Impairment $c_{impair,0}$

Considering that people often keeps their motivation in a small variation cite. Based on the results from the experiments on adjusting the state-transition matrix, this time

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Table 6.3: Position of dangerous epoch with respect to three different motor impairment

$c_{impair,0}$	Dangerous epoch in states $[s_1; s_2; s_3]$
1.2	[2; 0; 0]
1.5	[20; 10; 0]
2.0	[85; 61; 37]

when we change $c_{impair,0}$ we assigned other parameters with the following values,

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix};$$

$$U_p^{limbchoice} = 0.1; [\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]; \gamma = 0.95$$

With these settings of parameters, we conducted the experiments and the results were recorded in Table 6.3.

Results III: Changing Perceived Benefits $U_p^{limbchoice}$

To do the experiments in this session, we fixed the values of other parameters as following,

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix};$$

$$c_{impair,0} = 2.0; [\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]; \gamma = 0.95$$

The consequent results of dangerous epochs e_d for all states when we adjusted the value of $U_p^{limbchoice}$ according to the range given in Equation 6.8, were plotted in Fig. 6.1. For the small value of $U_p^{limbchoice}$,

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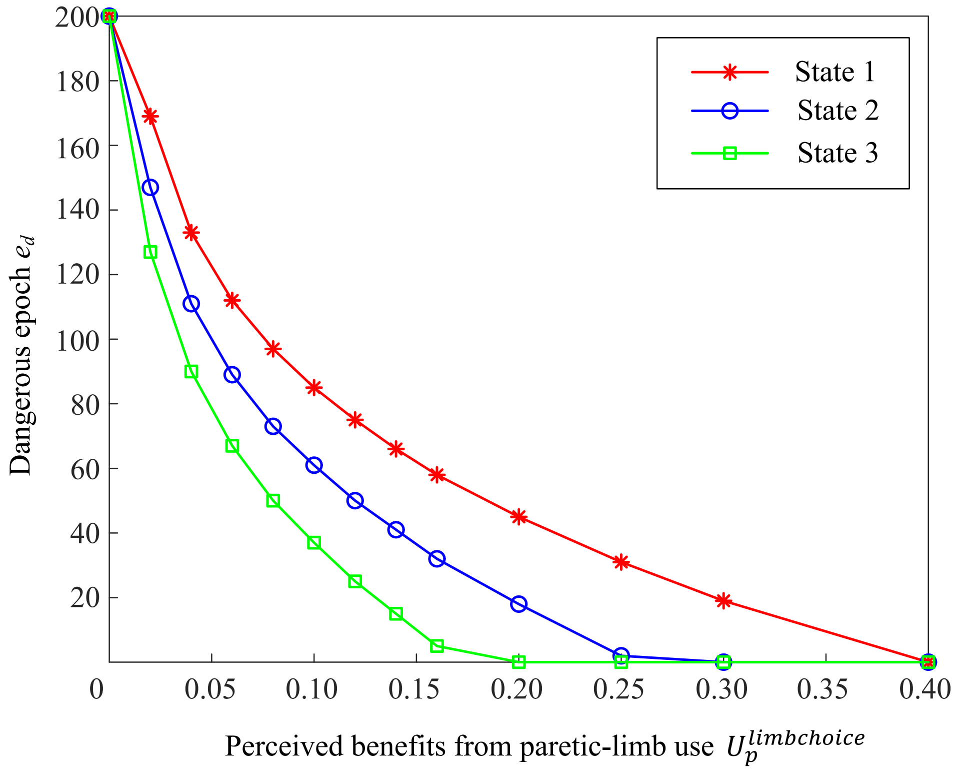

Figure 6.1: Influence of variation in $U_p^{limbchoice}$ on the position of dangerous epoch

Results IV: Changing Weight Vector $[\alpha_1; \alpha_2; \alpha_3]$

In this experiment session, we assigned all the variables except the weight vector with the following corresponding value,

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix};$$

$$c_{impair,0} = 2.0; U_p^{limbchoice} = 0.1; \gamma = 0.95$$

and then adjusted the values of pair $[\alpha_1, \alpha_3]$ and plotted the resulted dangerous epochs for three states, as shown in Fig. 6.2.

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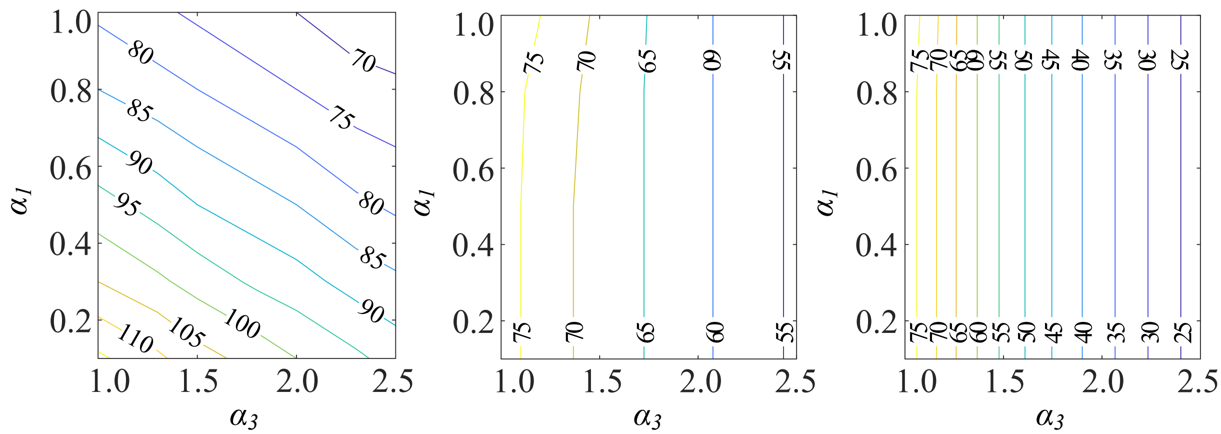

(a) State 1 **(b)** State 2 **(c)** State 2

Figure 6.2: Influence of variation in α_i on the position of dangerous epoch for State 1 (left), State 2 (middle), and State 3 (right)

Results V: Changing Discount Factor γ

Similar to previous experiments, we firstly fixed the following values, and then changed the value of discount factor γ and plotted the consequent effects, as shown in Fig. 6.3.

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix};$$

$$c_{impair,0} = 2.0; U_p^{limbchoice} = 0.1; [\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]$$

6.1.3 Discussion

In this subsection, we will investigate the effects of the variables, P, $c_{impair,0}$, $U_p^{limbchoice}$, $[\alpha_1; \alpha_2; \alpha_3]$, and γ, whose magnitudes we changed. The detailed discussion is presented in the following.

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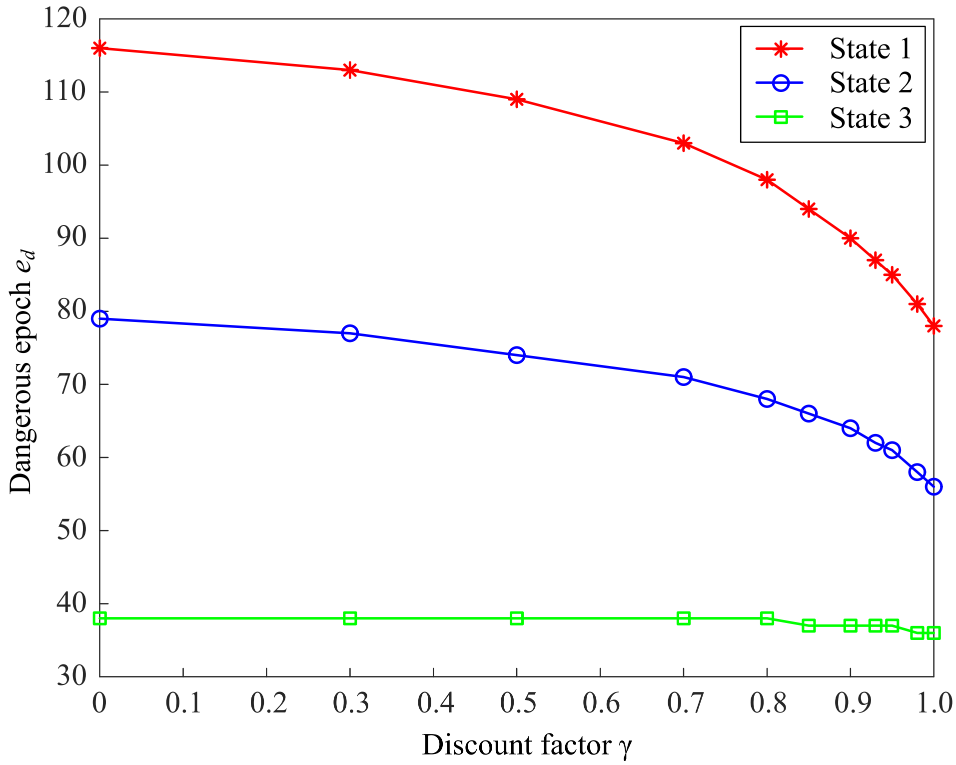

Figure 6.3: Influence of discount factor γ on the position of dangerous epoch

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Influence of State-Transition Matrix P

First of all, as show in Table 6.2, there were one generality among all cases: the higher motivated an individual is, the smaller dangerous epoch e_d he/she will have, for example, in the random (or converging into s_1 or highly tend to stay in current state) case, e_d for State 1, 2 and 3 is 116 (or 106 or 85), 79 (or 78 or 61), and 38 (or 38 or 37), respectively. This indicates that it will be less challenging and greater potential for a person with higher motivation, to adhere to the paretic-limb use in physical activity and thus get a better recovery outcome. This is exactly what people have found in previous studies, that is, a patient being more motivated to use the paretic limb, showed a better adherence to the prescribed exercise program and thus got a better recovery outcome [36,107,157,158]. From this standpoint, the MDP model we developed is capable of describing patients' dynamic behavior of limb choice with the influence of motivation level. Furthermore, based of this general result that a higher-motivated state (e.g. State 3) is associated with a smaller e_d, we suggest that intervention could be provided to help patients in a higher-motivated state, so that it is more potential for patient to adhere to using their paretic limb. Actually this is the central point highlighted by motivational games for stroke rehabilitation [159].

Among all the seven cases in Table 6.2, the case that an individual transit into any state in a totally random way showed the comparatively largest dangerous epoch e_d of 116, 79 and 38 for all three cases, which indicates that in this case it is the most challenging for patients to adhere to using their paretic limb as prescribed. For the second type that patients are always converging to one state, it seemed that they have very similar results, that is, the magnitude of dangerous epochs e_d associated with State 1, 2 and 3 in these three cases are approximately the same. However, from statistical perspective, the case of conversing into 1, 2 and 3 represents totally different nature/fact that patients are highly possible to be in State 1, 2 or 3, separately. Take, the case of converging into s_1 and s_3, as the example. In the former case, roughly speaking, there is a 80% probability during the recovery process that the patients is in State 1 and further is associated with a dangerous epoch $e_d = 106$. Comparatively, in the latter case, roughly speaking, there is a 80% probability during the recovery process that the patients is in State 3 but is associated with a small dangerous

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epoch $e_d = 38$. Definitely, the former case is far more challenging and difficult for a patient to adhere to using the paretic limb. Therefore, for the specific type of patients always converging into one state, "enforcing" patients in a higher-motivation state is still significant for them to practice the paretic limb and obtain a better stroke recovery.

Influence of Initial Motor impairment $c_{impair,0}$

Given that other parameters are the same, the effects of initial motor impairment on the dangerous epochs are listed in Table 6.3. Due to the identical state-transition matrices in this session, we can ignore the issue of which state patients may possibly be in. Notably, no matter which state patients are in, a milder initial stroke severity, that is, a smaller-magnitude $c_{impair,0}$, leads to a smaller dangerous epoch e_d and thus a shorter dangerous period P_d. Take an example of patients being in State 2, the dangerous epoch does not exist for patients with $c_{impair,0} = 1.2$, while $e_d = 10$ and 61 for patients with $c_{impair,0} = 1.5$ and 2.0, separately. The reason why the parameter $c_{imapir,0}$ have a negative effect on e_d is that generally the initial motor impairment dominantly influence patients' disease progression, that is, our motor recovery curve. At the same time point t from stroke onset, a larger $c_{impair,0}$ is generally associated with a greater $c_{impair}(t)$ [75, 151–155], which will lead to a lower reward component of task performance $U_p^{taskperform}$ (considering the arm plant model we applied). This resulted $U_p^{taskperform}$ captures a lot of information associated with stroke patients during the physical activities in daily life from both physiological and psychological perspective, such as the decreased range of motion and slow movement over time, and also the possible pain, depression, and low self-efficacy and outcome expectation due to the motor and functional disability [35, 36, 108].

As we mentioned before, a greater-magnitude e_d indicates that it is more challenging for a patient to adhere to use the paretic limb and worsely this challenging period is also longer, which is a big problem that patients with severe stroke severity have to face. From this perspective, more effort (i.e., time and treatment) should be provided for people with a more severe motor impairment than those with a milder motor impairment. Actually this strategy has been adopted by most hospitals. Usually patients merely with mild severity would not be admitted by hospitals, but treated as outpatients [23]. Furthermore, we also

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think this is suggestive in constructing the future adaptive intervention for chronic stroke rehabilitation or home-based tele-rehabilitation, in which more effort,care and time should be provided for patients initially attacked by a more severe stroke.

Influence of Perceived Benefits $U_{limb}^{limbchoice}$

The magnitude of $U_{limb}^{limbchoice}$ reflects how good/valuable patients perceive from using their paretic limb for their stroke recovery, overall health and reduction in the risk of secondary stroke, etc. The three curves in Fig. 6.1 showed that in our Markov decision process modelling, the variable $U_{p}^{limbchoice}$ has a visible, positive influence on the optimal decisions for all states, that is, an increment of perceived benefits will lead to a decreases in the dangerous epoch e_d. This indicates that the improvement of patients' perceived benefits can help patient to better adhere to the paretic-limb use, which conincides with the previous study. People found that patients post-stroke who didn't identify the benefits of exercising showed low adherence to the training program [36, 106, 142, 158]. Therefore, our model is able to represent the effects of patients' perceived benefits on patients' adherence to the paretic-limb use during physical activities. Moreover, in Fig. 6.1, as the perceived benefits $U_{p}^{limbchoice} \approx 0$, the dangerous epochs e_d associated with three states are all very large, indicating that it would be very challenging and nearly impossible for patients to follow the prescribed exercise of the paretic limb. The extreme case is that $U_{p}^{limbchoice} = 0$, which indicates that patients totally have no idea on the benefits of exercise on stroke recovery. In this situation, patients would only care about their psychological and physical sensations during performing task and from this perspective the non-paretic limb will always outperform the paretic limb. As a result, patients would always use their non-paretic limb in daily life, which is exactly the same to our results (i.e., $e_d = 200$ in all three states).

Stroke patients' perceived benefits $U_{p}^{limbchoice}$ of using paretic limb can be influenced or adjusted by their external environments, such as family, community and related education [147, 160]. Based on our finding, we suggest that during rehabilitation process, education including the importance of paretic-limb use on stroke recovery and health should be provided for patients so that they can identify the benefits of adherence to paretic-limb use, which would promote patients in using their paretic limb. Interesting, as we increase the magnitude

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of perceived benefits, all the curves turned to be less steep, which can be understood from two perspectives. On one hand, when the perceived benefits $U_p^{limbchoice}$ is in a range of small values, for example, $(0, 0.15)$, the slope of curves is much steeper, which suggests that a small decrease in $U_p^{limbchoice}$ could lead to a distinct increase in the dangerous epoch e_d and thus the challenge for patients adhering to paretic-limb use. Therefore, during rehabilitation process we need to particularly pay attention to patients' perceived benefits and provide some intervention if necessary to prevent from the decrease of $U_p^{limbchoice}$ and from worsening patients' rehabilitation. On the other hand, when the perceived benefits become large enough, for example, $U_p^{limbchoice} \in [0.2, 0.4]$, the curve slopes will be less and less steep, which suggests that the effectiveness of perceived benefits enforcing patients' adherence is decreasing. This is especially meaningful to the construction of cost-effective interventions for stroke rehabilitation for future health care system. In other words, in clinical application, we should not merely consider increasing patients' perceived benefits, in order to help patients to perfectly follow the exercise program. Instead, we need to take both the effectiveness of $U_p^{limbchoice}$ and the cost of providing this $U_p^{limbchoice}$ into consideration.

Influence of Weight Vector $[\alpha_1; \alpha_2; \alpha_3]$

During this experiment, we totally proposed 35 pairs of (α_1, α_1) to explore the effects of weight vector, $[\alpha_1; \alpha_2; \alpha_3]$, on optimal policy (or patients' limb choice). The results were plotted in the form of contour in Fig. 6.2. The subfigure 6.2a, 6.2b, and 6.2c correspond to State 1, 2, and 3, respectively. The numbers marked in the contour denote the dangerous epoch e_d with some specific combination of $[\alpha_1; \alpha_2; \alpha_3]$. For example, take the figure 6.2a as an example, with $[\alpha_1; \alpha_2; \alpha_3] = [0.8; 1.0; 2.0]$, the dangerous epoch e_d in State 1 is 75. Compared to Fig. 6.2a, the contours in Fig. 6.2b and 6.2b are almost vertical lines, which can be understood as that the dangerous epochs in State 2 and 3 are almost independent of α_1. This is caused by our setting of state-transition matrix, which maps to the case of patients tending to stay in the current state. This also explains that the contours in Fig. 6.2c is more intense than those in Fig. 6.2b.

Fig. 6.2a showed that the dangerous epoch e_d in State 1 is influenced by α_1 and α_3 simultaneously. More specifically, the increase in either α_1 or α_2 can decrease e_d. From this

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finding, we may also particularly pay attention to a patient's status in State 1, that is, how good this individual think about using paretic limb in State 1. If it is totally not significant to him/her, the individual could be more impossible to adhere to paretic-limb use.

Influence of Discount Factor γ

We investigated the full potential range of discount factor γ. As expected, a larger γ will lead to a smaller dangerous epoch e_d, especially in State 1 and 2, as shown in Fig. 6.3. This is feasible considering that a larger discount factor γ (or more approaching to 1), indicates the patient is more far-sighted and the futures rewards (motor recovery) is more valuable at the current time point. Interestingly, the effect of γ on patients' adherence increases as γ approaches to 1, for example, the range of $[0.8, 1.0]$. Mathematically speaking, if γ is not large enough, the future rewards at the current decision epoch are nearly 0 and therefore play a negligible role in making decisions. On the other hand, when γ is large enough, any further increment in γ will make the future accumulated rewards more significant compared to the immediate reward, and therefore plays an important role. However, compared to other parameters such as perceived benefits, the ability of influencing the optimal decisions by the discount factor is limited.

6.1.4 Summary

In Section 6.1, to confirm the ability of our Markov decision process (MDP) model to represent the primary mechanism underlying chronic stroke patients' behavior of suppression of paretic-limb use, we changed the values of five main variables (i.e., P, $c_{impair,0}$, $U_p^{limbchoice}$, $[\alpha_1; \alpha_2; \alpha_3]$, and γ) and analyzed the consequent effects. Our Markov model showed good performance in understanding the potential factors controlling (i.e., motivating or preventing) patients making decisions on limb choice during the rehabilitation process.

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6.2 Experiment II: Interventions on Dynamic Limb Choice

Having validated our Markov decision process (MDP) model, we further applied this model to explore the effectiveness of potential interventions. In this section, we explicitly proposed twp types of intervention, which might be achieved in clinical practice, and evaluated their effectiveness using our MDP. Later we showed how we could translate these interventions into clinical application.

6.2.1 Specification of interventions

The experiment for comparison is still with the following setting,

$$P(:,:,1) = \begin{bmatrix} 0.75 & 0.24 & 0.01 \\ 0.05 & 0.80 & 0.15 \\ 0.01 & 0.14 & 0.85 \end{bmatrix}, P(:,:,2) = \begin{bmatrix} 0.90 & 0.09 & 0.01 \\ 0.15 & 0.80 & 0.05 \\ 0.01 & 0.24 & 0.75 \end{bmatrix};$$

$$c_{impair,0} = 2.0; U_p^{limbchoice} = 0.1; [\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]; \gamma = 0.95$$

And the associated dangerous epoch e_d for three states are $[85; 61; 37]$. To ensure that patients can adhere to paretic-limb use during rehabilitation process, we would consider the worst case, that is, State 1 of low motivation. Therefore, we take the dangerous period of State 1, $P_d = e(1:85)$, as the baseline of intervention period. Finally, we chose the intervention period as $P_I = e(1:85)$.

Inventions with a role of $U_p^{taskperform}$

This intervention is provided in the form of $\Delta U_p^{taskperform}$. For example, if the intervention $\Delta U_p^{taskperform} = 0.1$ is provided, in each epoch during $e(1:85)$ the immediate reward from task performance is now updated as

$$U_{p,total}^{taskperform} = U_{p,original}^{taskperform} + \Delta U_p^{taskperform} \tag{6.9}$$

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where the right, first term $U^{taskperform}_{p,original}$ represents the reward from task performance by patients' own physiological ability. As a result, the left term in Equation 6.9 denotes the total reward from task perfromance with the help of intervention. Currently, the range of $\Delta U^{taskperform}_p$ we designed for investigation is shown as following

$$\Delta U^{taskperform}_p = \{0, 0.010, 0.030, 0.050, 0.080, 0.100, 0.125, 0.150, 0.175, \\ 0.200, 0.225, 0.250, 0.300\}$$

Inventions with a role of $U^{limbchoice}_p$

Similarly, we also provided intervention in the form of perceived benefits, $\Delta U^{limbchoice}_p$. As a result, we have the new perceived benefits in a task expressed as following,

$$U^{limbchoice}_{p,total} = U^{limbchoice}_{p,original} + \Delta U^{limbchoice}_p \tag{6.10}$$

The right, first term represents the perceived benefits from paretic-limb use, and the right, second term represents the intervention provided for patients. Similar to the invention experiment of $\Delta U^{taskperform}_p$, the intervention $\Delta U^{limbchoice}_p$ would only provided in the period $P_d = e(1:85)$. We designed the magnitude of this intervention as

$$\Delta U^{limbchoice}_p = \{0, 0.0001, 0.0005, 0.0008, 0.0010, 0.0015, 0.002, 0.0022, \\ 0.0023, 0.0024, 0.0025, 0.0030, 0.0032, 0.0033, 0.0034, 0.0035\}$$

6.2.2 Results and Discussion

Effect of Intervention $\Delta U^{taskperform}_p$

We provided each of the predesigned intervention during the intervention period P_d and the influence on patients' behavior of adhering to paretic-limb use, (i.e., the dangerous epoch e_d), is recorded in Fig. 6.4. In this figure, the red asterisk line, the blue circle line and the green square line corresponds to the situation of patients being in State 1 (low motivation), State 2 (moderate motivation) and State 3 (high motivation). As we can see, the dangerous epoch

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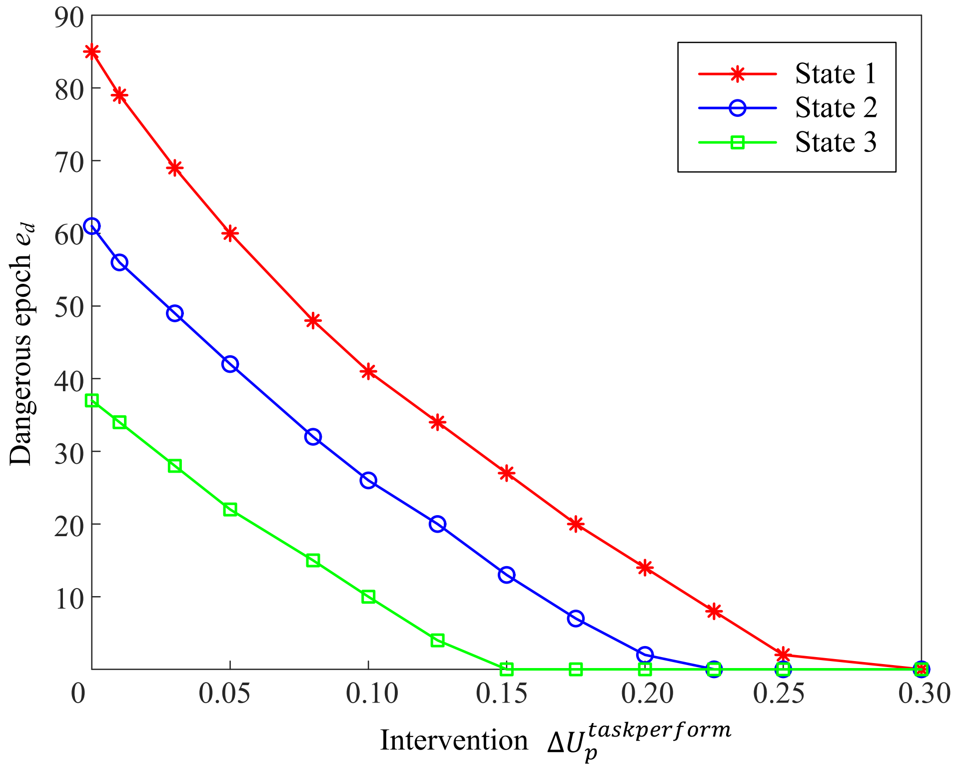

Figure 6.4: Effects of intervention $\Delta U_p^{taskperform}$ on patients' optimal policy

e_d decreases as we increase the magnitude of intervention $\Delta U_p^{taskperform}$, which suggests that the intervention $\Delta U_p^{taskperform}$ is capable of helping patients to have a better adherence to the prescribed exercise of paretic limb and further to obtain a better stroke recovery.

Practically, a number of therapies can be understood us playing the role of $\Delta U_p^{taskperform}$ during stroke rehabilitation. For example, the robot-assisted therapy. Through modulating the output impedance or the interaction with patients [37, 161–164], these robots help patients, from a physical perspective, to improve their range of motion, coordination and posture stability, and further from a psychological perspective, to reduce the potential pain, fatigue and depression. Notably, there is also the issue of cost-effectiveness associated with this intervention. As shown in Fig. 6.9, the slope of the curve in any state becomes less steep as the magnitude of $\Delta U_p^{taskperform}$ increases, which indicates that its effectiveness on motivating patients to use their paretic limb decreases. Therefore, in real world, we should take both the effectiveness and the cost of $\Delta U_p^{taskperform}$ into consideration during the design of adaptive intervention for chronic stroke patients.

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Effect of Intervention $\Delta U_p^{limbchoice}$

In this series of experiments, we provided the pre-designed intervention $\Delta U_p^{limbchoice}$ for individuals during the intervention period P_d. The associated results are shown in Fig. 6.5. The red, blue and green curves correspond to the state s_1, s_2 and s_3. Obviously, the intervention $\Delta U_p^{limbchoice}$ has a positive effect on patients' adherence to paretic-limb use. In the ideal case where we can provide large enough intervention, patients would follow the exercise program perfectly, for example, when the invention $\Delta U_p^{limbchoice} = 0.0035$, the dangerous epochs e_d for all states becomes 0, which suggests that patients will 100% adhere to their paretic-limb use in physical activity. For clinical application, the intervention $\Delta U_p^{limbchoice}$ here can be provided by means of more education on stroke and the benefits of practicing paretic-limb on stroke rehabilitation, which can achieved by family, rehabilitation center or community [147, 160].

Interestingly, for an identical intervention $\Delta U_p^{limbchoice}$, its effectiveness on patients is different among different states. For example, when provided the intervention $\Delta U_p^{limbchoice} =$

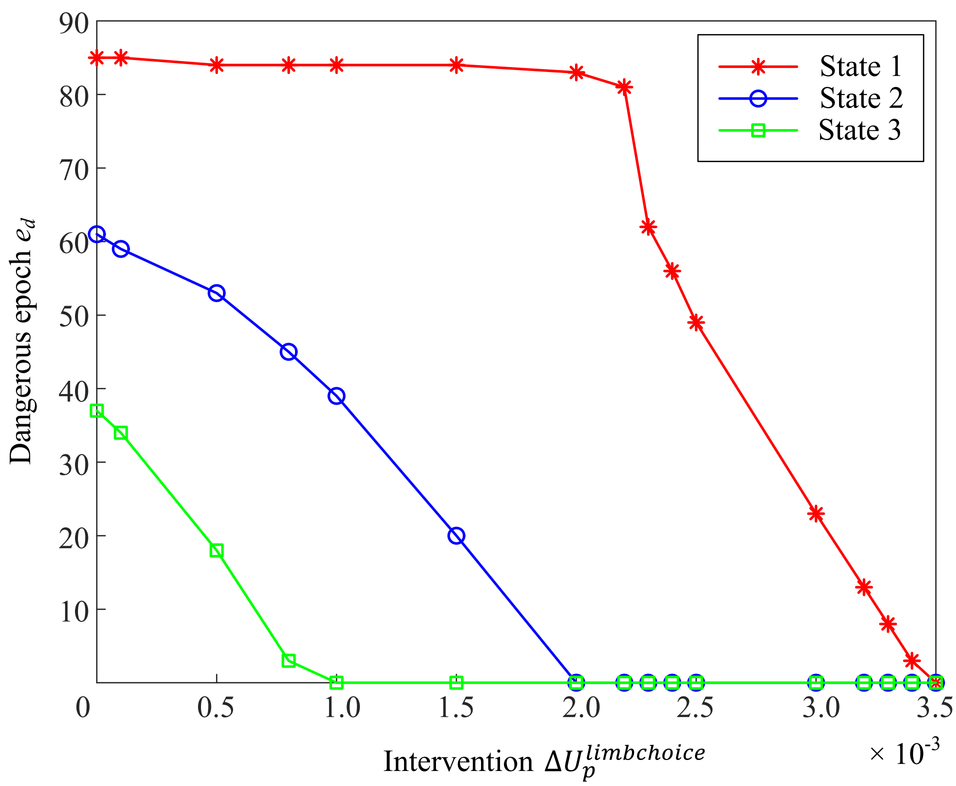

Figure 6.5: Effects of intervention $\Delta U_p^{limbchoice}$ on patients' optimal policy

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0.0015, the dangerous epoch e_d for state s_1, s_2 and s_3 are 84, 20 and 0, respectively. Compared to the case without any intervention where $e_d = [85, 61, 37]$, it can be seen that the influence on the optimal decisions of patients in State 2 and 3 is visible, while the influence on State 1 is negligible. This is very meaningful in real-world application. Generally cannot ensure that a patient would always be in State 3 of high motivation, especially for a post-stroke patient suffering from negative emotions such as depression and low self-efficacy. As a result, we should particularly take State 1 into consideration. Actually Fig. 6.5 is also a reflection of Fig. 6.2a, in which even the weight factor α_3 has became very large (e.g., 2.5), if the weight factor α_1 is not large enough (e.g., 0.2, 0.2), the associated dangerous epoch could still be very large. Now in our study of intervention $\Delta U_p^{limbchoice}$, we fixed the weight vector $[\alpha_1; \alpha_2; \alpha_3] = [0.5; 1.0; 2.0]$. The small value $\alpha = 0.5$ explains why the influence by intervention $\Delta U_p^{limbchoice} \in (0, 0.0020)$ is so small. This suggests that in clinical practice we may put more effort to improve patients' specific perceived benefits (that is, the weight factor α_1) in State 1 or to help patients away from State 1, instead of merely focus on providing a greater-magnitude intervention of $\Delta U_p^{limbchoice}$.

6.3 Conclusion

In this chapter, we validated our Markov decision process (MDP) by modulating the value of five crucial variables, that is, state-transition matrix P, initial motor impairment $c_{impair,0}$, perceived benefits of paretic-limb use $U_p^{limbchoice}$, weight vector $[\alpha_1; \alpha_2; \alpha_3]$ and discount factor γ, and evaluating the consequent influence on human behavior, i.e., optimal decisions of limb use. Our model showed good performance on the analysis of how these variables influence (motivate or prevent) patients dynamic limb choice. Generally, an individual, in a higher motivated state, a milder initial motor impairment, a greater perceived benefits and a greater discount factor, is more potential to adheren to use the paretic limb. In terms of clinical practice, we suggest that interventions which are able to help patients in a higher-motivated state, and/or increase the reward from performing task by paretic limb, and/or help patients identify the benefits of using paretic limb on health, should be considered, for example, the behavior intervention, the education on the importance of paretic-limb use on stroke

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recovery and health. Therefore, our model may offer great potential for the design of adaptive intervention for stroke rehabilitation. Moreover, the model we developed here may also be applied to understand other human behaviors during the chronic disease progression.

There are three main limitation that may reduce the performance by our model. The first one is the ideally, simplified motor recovery curves, which is a determinant part of our reward function. One of the main reason that there is only one dangerous epoch is that our motor recovery curve is a monotonously decreasing function. The second limitation is in the constant perceived benefitc $U_p^{limbchoice}$, which was suggested to change over time in some papers [147]. Finally, the third weakness is a common challenge faced by the research of chronic disease, lack in longitudinal data to validate data. More study in terms of these three weakness will be conducted in future.

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Chapter 7

Conclusion and Future Work

In this paper, we developed a pendulum-based physical model to mimick human upper-extremity dynamics in a shoulder flexion task and further proposed a torque-based metric to quantify the motor performance across limbs (paretic and non-paretic) and across individuals (healthy and post-stroke). Later we implemented a Markov decision process (MDP) to model human behavior of decision making (or limb choice) for physical activity during the post-stroke rehabilitation process and explored the potential controlling forces (motivator or barriers) underlying this human behavior.

The pendulum-based dynamical model demonstrates the ability to quantify a proxy for the limb with only one variable, joint torque τ. For the paretic arm of individuals post-stroke, it is reasonable to take this ability as its maximal motor ability. The preference of non-paretic arm to paretic arm in daily life suggests that for healthy people there may be also an underlying comparison of challenge/effort required for each limb during decision-making process, i.e. limb choice. In this term, our pendulum-based plant model provides a possible, torque-based approach to investigate this dynamical decision-making process and to predict limb choice. τ can be taken as a simplified quantification of effort required by the motion for one arm. And this parametric dynamic model, which is simple but efficient, can play the role of system identification, whose significance has been emphasized in behavioral science, e.g. the energy balance model during gestational weight gain [57], and the *Craving-Sigsmked* interrelationship in the smoking behavior [58].

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Moreover, with the ability to measure and quantify post-stroke severity, our dynamical system model can be applied as a convenient, reproducible approach to monitor time-varying UE motor impairment after stroke, in kinetics terms based on patients' kinematics information, which can be easily collected by wearable sensors or IMUs. And the output of model, w_p^{stroke}, is representative of stroke severity. This shows great convenience in a wide application of investigating and monitoring the post-stroke disability, compared to those previous researches [75–80]. Furthermore, this standardized approach provides a promising future for the adaptive intervention of post-stroke rehabilitation. With access to the ongoing kinematics of individuals post-stroke, the dynamical system model figures out the output w_p^{stroke}, which can be taken as the *tailoring variable* and indicate the adjusting intervention through the decision rules. Therefore, this will be a fundamental step for a powerful and cost-efficient adaptive intervention for post-stroke rehabilitation.

Our Markov decision process (MDP) showed good performance on the analysis of the controlling factors underlying post-stroke patients' suppression of the paretic limb use in daily life. Primarily, individual motivation, perceived benefits of paretic-limb use for stroke recovery and health, and initial motor impairment (or motor recovery during disease progression) all have crucial influence on the optimal decisions patients make on limb choice during their daily life. In terms of clinical practice, we suggest that interventions which are able to help patients in a higher-motivated state, and/or increase the reward from performing task by paretic limb, and/or help patients identify the benefits of using paretic limb on health, should be considered, for example, the behavior intervention, the education on the importance of paretic-limb use on stroke recovery and health. Therefore, our model may offer great potential for implementing cost-effective adaptive intervention for stroke recovery, such as home-based rehabilitation program. Moreover, the model we developed here may also be applied to understand other human behaviors during the chronic disease progression.

As we mentioned in previous chapter, in future we will try to extend our study to a larger population and a longitudinal design, to improve the performance of our model in representing and describing human behaviors in real world. Moreover, currently our dynamical system model is based on a two-dimension, upper-extremity physical model which is constrained to the motion of shoulder flexion, therefore, our future work will also focus

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on the application of the idea behind our dynamical system model into daily life, which is meaningful to the design of home-based rehabilitation combining adaptive intervention. Finally, inspired by the possible effective interventions for stroke rehabilitation in our MDP study, we will also work on how to map and translate these numerical values into real-world clinical application, so that we could develop a cost-effective intervention for stroke rehabilitation in future.

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