Modeling and FES control of human movement with threshold control theory

Lan, Li

2011

Lan, L. (2011). Modeling and FES control of human movement with threshold control theory. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/45772>

<https://doi.org/10.32657/10356/45772>

Modeling and FES Control of Human Movement with Threshold Control Theory

Lan Li

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2011

Acknowledgements

The road to Ph.D. is thorny, yet definitely rewarding. It would be impossible for me to reach here without the support of many people.

Firstly, I would like to present my deepest gratitude to my supervisors, Dr. Wen Changyun and Dr. Zhu Kuanyi, for their valuable advices and warm encouragement. Dr. Wen has given me a great deal of intellectual freedom. His patience and help is essential for preparing this thesis. Dr. Zhu has given me many helpful guidance in my research career. His positive working attitude inspired me significantly. My gratitude also goes to Prof. A.G. Feldman for his helpful comments and useful suggestions on the threshold control theory.

I enjoyed the companionship with my fellow students and staffs in the Biomedical Instrumentation Laboratory and thank all of them for helping me over so many years. In particular, I want to thank Zhang Dingguo for the advices regarding to the musculoskeletal system model, human walking and central pattern generator; I thank Chen Ming for the ultrasound signal processing; I also thank Yang Xin and Yap Sing Loon for valuable technical support in my research.

Specially, I would like to thank my parents, who always tell me to do my best, and to believe in myself. I would like to thank my wife, Miao Huang, whose love never fails to motivate me to persevere in the tough moments. I also would like to

thank my daughter, Lan Miaochen Aurora, who was born on April 09, 2011. This beautiful angel led me into the new phase of my life.

Last but not least, I acknowledge Nanyang Technological University for the valuable opportunity of my Ph.D. study with financial support in Singapore.

April 25, 2011

Lan Li

Table of Contents

Acknowledgements	ii
Summary	ix
List of Abbreviations and Symbols	xi
List of Figures	xv
List of Tables	xviii
1 Introduction	1
1.1 Background	1
1.2 Synopsis	3
1.2.1 Subject-specific musculoskeletal model	4
1.2.2 Verification and modification of threshold control theory	4
1.2.3 Study of threshold FES control system	5
1.3 Contribution	6
1.4 Organization of the thesis	8

2	Literature Review	9
2.1	Central nervous system	10
2.1.1	Introduction of spinal cord	12
2.1.2	Neuronal network of spinal cord	12
2.2	Musculoskeletal system and muscle properties	14
2.2.1	Physiological properties of muscle	15
2.2.2	Mechanical properties of muscles	17
2.2.3	Receptors of muscles	19
2.3	Modeling of neuromusculoskeletal system	20
2.3.1	Modeling of neural circuits	21
2.3.2	Muscle model	24
2.4	Motor control	25
2.4.1	Problems in motor control	25
2.4.2	Threshold control theory (λ -model)	27
2.4.3	Control strategies of FES	28
3	Development of Subject-specific Musculoskeletal Model	32
3.1	Introduction	32
3.2	Musculoskeletal system model	34
3.2.1	Activation dynamics	36
3.2.2	Contraction dynamics	37
3.2.3	Tendon compliance	38
3.2.4	Anatomical arrangement	39
3.2.5	Joint dynamics	42
3.3	Model parameters estimation	43
3.3.1	Estimation of insertion and origin	45

3.3.2	Estimation of optimal muscle fascicle length	47
3.3.3	Estimation of maximum isometric force	49
3.4	Experimental protocol	51
3.5	Results	52
3.5.1	Estimated parameters	52
3.5.2	Prediction of maximum voluntary isometric torque	54
3.6	Discussion & Conclusion	55

4 Verification of Threshold Control Theory on Single Joint Movements 56

4.1	Introduction	56
4.2	Control scheme	59
4.3	Experimental method	64
4.3.1	Experimental protocol	64
4.3.2	Data collection and analysis	64
4.4	Experiment and simulation results	66
4.4.1	Verification of the threshold control model and two extensions	67
4.4.2	Robustness to feedback delay and perturbations	77
4.4.3	Influence of subject-specific musculoskeletal parameter	78
4.4.4	Conclusion of experimental and simulation study	81
4.5	Discussion	81
4.5.1	Validity of threshold control theory	81
4.5.2	Difference from the latest threshold control model	83
4.5.3	Performance of extensions	85
4.5.4	Sensitivity of feedback gain	86

4.5.5	Further improvement of threshold control theory	88
4.6	Qualitative analysis of system stability	88
4.6.1	Stability analysis of simplified model	90
4.6.2	Simplified model with external load	97
4.6.3	Simplified model with joint viscosity	98
4.6.4	Simplified model with time delay	99
4.6.5	Conclusion of qualitative stability analysis	100
4.7	Conclusion	100
5	Development and Verification of Threshold FES Controller on	
	Upper Limb Movement	102
5.1	Introduction	102
5.2	Study of single joint model	105
5.2.1	System description	105
5.2.2	Simulation results	113
5.2.3	Discussion on operation range and feedback delay	118
5.2.4	Brief summary	119
5.3	Study on two joints model	121
5.3.1	System description	121
5.3.2	Simulation results	130
5.4	Discussion	134
5.5	Conclusion	140
6	FES Control for Two-dimensional Human Walking by Threshold	
	Controller and Central Pattern Generator	141
6.1	Introduction	141
6.2	System description	143

6.2.1	Musculoskeletal system	144
6.2.2	Central pattern generator	147
6.2.3	Threshold controller	149
6.3	Simulation results	150
6.3.1	CPG-controller	151
6.3.2	CPG-threshold controller	151
6.3.3	Speed control	152
6.3.4	Perturbation	154
6.4	Discussion and conclusion	156
6.4.1	Physiological roles of CPG and the threshold controller	156
6.4.2	Rhythmic movement and monotonic movement	157
6.4.3	Speed control	157
6.4.4	Feedback delay and posture control	158
6.5	Conclusion	158
7	Conclusion and Future Work	159
7.1	Conclusion	159
7.2	Future work	161
7.2.1	Control of the multiple degrees of freedom system	161
7.2.2	3D musculoskeletal model	162
7.2.3	Ultrasound elastography for parameters measurement	162
	Author's Publications	164
	Bibliography	168
	Appendix	I

Summary

Our study aims to build a physiology-based control model of the human motor system. In the perspective of control engineering, an ideal controller is expected to drive the complex motor system without solving the “inverse dynamics problem”. Thus many researchers have suggested that the threshold control theory might be a good candidate to build such a controller.

However, the physiological relevance of threshold control theory is still under debate. So we first validate the threshold control theory by simulation and experimental studies. A subject-specific musculoskeletal model is developed to conduct simulation study. To ensure the credibility of the simulation, the parameters are measured *in vivo* with ultrasonography. The results of simulations and experiments are compared. The comparisons suggest that the controller based on threshold control theory can ideally drive the physiology-based musculoskeletal system to 1) realize desired movements with different feedback delays; 2) generate the muscle stimulation/excitation ; 3) reproduce corresponding muscle activation patterns.

Secondly, we incorporate the threshold control theory to the artificial motor control system. e.g., the functional electrical stimulation (FES) system. In detail, the threshold FES controller is designed based on threshold control theory to control the electrical stimulation pulse width. Simulation studies of single joint

movement suggest that the threshold FES controller is able to realize basic functions, however better robust to feedback delays and external perturbation can be achieved by introducing the feedback of joint angular acceleration to threshold FES controller. Further simulation results of two joints movement prove that the improved threshold FES controller can realize desired task in multi-joints system with various feedback delays and external loads as well.

Furthermore, we try to integrate the central pattern generator (CPG) and threshold FES controller to realize artificial human walking. The study suggests that although the CPG can independently generate rhythmic motor patterns in the absence of sensory feedback, an additional threshold controller can modify the output excitations to generate a smoother walking pattern. Moreover, it is approved that the integrated controller is adaptive to various feedback delays and perturbations.

List of Abbreviations and Symbols

Abbreviations

CNS	central nervous system
CPG	central pattern generator
GTOs	Golgi Tendon Organs
FES	functional electrical stimulus
DOF	degrees of freedom
CE	contractile element
PE	parallel-elastic element
SE	series-elastic element
PID	proportional-integral-derivative
CT	computerized tomography
MRI	Magnetic Resonance Imaging
PCSA	physiological muscle cross-sectional area

MVC	maximum voluntary isometric contraction
OML	optimal muscle-fiber length

Glossary

Subscript:

f	Flexor muscles
e	Extensor muscles
mf	Mono-articular elbow flexor (Biceps long head)
me	Mono-articular elbow extensor (Triceps Lateral head and Medial head)
bra	Brachialis
bf	Biarticular Flexor (Biceps short head)
be	Biarticular Extensor (Triceps long head)
o	Optimal value
max	Maximum value
sh	Shoulder joint

Superscript:

M Muscle

CE Contractile element

PE Passive elastic element

MT Muscle-tendon complex

T Tendon

Threshold controller:

λ Static threshold

λ^* Dynamic threshold

R Reciprocal command

C Co-activation command

t_d Feedback time delay

Activation dynamics:

E Muscle excitation.

A Muscle activation

Contraction dynamics:

F Force

L Length

V velocity

$\tilde{L}, \tilde{V}$ Normalized length/velocity

L_s^T Tendon slack length

α_p Pennation angle

Anatomical arrangement and joint dynamics:

θ Joint angle

ω Joint angular velocity

ξ Joint angular acceleration

h Moment arm

T Torque

T_L External Torque

I Moment of inertia

B Coefficient of viscosity

Remark 1: The subscript and superscript can be composed to present a complicated meanings. For example, L_{o-mf}^M represents the optimal monoarticular elbow flexor muscle length.

Remark 2: The abbreviation of other parameters refer to the description of formulas.

List of Figures

2.1	The hierarchical diagram of the CNS mechanism.	11
2.2	Sketch map of tetanus.	16
2.3	Force-length relationship in fusiform muscle, where l_0 is the optimal muscle length.(Adapted from [1])	18
2.4	Force-velocity relationship (Adapted from [1]).	19
2.5	The signal flowchart of model of the neural circuits.	22
2.6	Hill's three elements mechanical model.	25
3.1	The geometric relations of the elbow.	35
3.2	The sketch map of musculoskeletal model.	36
3.3	Geometrical relationship of elbow muscles.	40
3.4	The procedure of parameters estimation for subject-specific musculoskeletal model by ultrasonography measurement.	44
3.5	Longitudinal ultrasonography shows the normal appearance of the long head of the biceps tendon.	46
3.6	Longitudinal ultrasonography of the medial aspect of the distal triceps insertion shows the tendon attachment to the olecranon.	47
3.7	The geometrical model of musculotendon complex.	48
3.8	The longitudinal view of the ultrasonography of brachialis and biceps brachii.	48

3.9	The transverse view of the ultrasonography of flexor muscle groups.	50
4.1	Threshold control of muscle excitation.	60
4.2	System block of the musculoskeletal model with the threshold controller.	62
4.3	System block of the threshold control model with feedback on the difference between the actual and desired velocities.	63
4.4	The estimation of muscle activation from sEMG	66
4.5	Experimental and simulated joint angles for normal movement. . . .	68
4.6	Experimental and simulated joint angular velocities for normal movement.	69
4.7	Experimental and simulated flexor muscle activations for normal movement.	70
4.8	Experimental and simulated extensor muscle activations for normal movement.	71
4.9	Experimental and simulated joint angles for fast movement.	72
4.10	Experimental and simulated joint angular velocities for the fast movement.	73
4.11	Experimental and simulated flexor muscle activations for fast movement.	74
4.12	Experimental and simulated extensor muscle activations for fast movement.	75
4.13	Simulated elbow joint angle with external perturbations for fast movement.	79
4.14	Simulated elbow joint angle and angular velocity with external perturbations for fast movement (continue Fig. 4.13).	80

4.15	The simulated elbow joint angle and angular velocity with the subject-specific model and the cadaver-based model for fast movement. . . .	82
4.16	The dynamic responses of the system for different values of μ	87
4.17	Three operation regions of threshold control model	94
5.1	The geometric relations of the elbow for FES single-joint movement.	107
5.2	Muscle actuator under FES stimulation	108
5.3	Block diagram of threshold FES control (Acc. FES controller). . . .	113
5.4	Simulation results of three threshold controllers with different feedback delays for FES single joint movement.	115
5.5	Simulation results of three threshold controllers with different feedback delays for FES single joint movement (continued to figure 5.4)	116
5.6	Simulated elbow joint angle and angular velocity with external perturbations for FES single-joint movement	117
5.7	The operation range of feedback gains μ and k_ξ to stable the FES single joint system with feedback delay.	120
5.8	Graphic representations of FES two-joint model.	122
5.9	Geometrically relationship of FES two-joints model.	124
5.10	The external force provided by spring or the pulse perturbation for FES two-joints model	127
5.11	The flowchart of FES control system for 7 muscles, two joints movement.	131
5.12	The simulation results of the FES controlled two joints movement with different feedback delays	133
5.13	Responses of FES two-joints model to external perturbations in the presence of feedback delays of 20 ms.	135

5.14	Responses of FES two-joints model to external loads in the presence of feedback delays of 20 ms.	136
6.1	Block diagram of the proposed FES controlled models for human locomotion.	145
6.2	Musculoskeletal model of human walking.	146
6.3	Bio-mechanical model of foot with action to ground.	147
6.4	The structure of CPG for walking control.	149
6.5	The output from CPG with 1 Hz rhythmic motor pattern.	150
6.6	Simulated joint angles of right limbs during walking by CPG-controller with 1 Hz rhythmic motor pattern.	152
6.7	Simulated joint angles of the CPG-threshold controller with 1 Hz rhythmic motor pattern.	153
6.8	Simulated stimulation patterns with CPG-threshold controller. . . .	154
6.9	Variation of locomotion speed.	155
6.10	Performance of CPG-threshold controller with external perturbation. Feedback delay $t_d = 30$ ms	155
A.1	Experiment photo of anthropometry	I
A.2	Experiment photo of biceps insertion measurement	II
A.3	Experiment photo of biceps origin (long head) measurement	II
A.4	Experiment photo of triceps insertion measurement	III
A.5	Experiment photo of brachialis insertion measurement	III
A.6	Experiment photo of brachialis origin measurement	IV
A.7	Experiment photo of biceps fascicle length measurement	IV
A.8	Experiment photo of triceps fascicle length measurement	V
A.9	Experiment photo of flexor's PCSA measurement	V
A.10	Experiment photo of extensor's PCSA measurement	VI

List of Tables

3.1	Anatomy of insertions and origins	46
3.2	Musculoskeletal model parameters	53
3.3	Maximum voluntary isometric torque	54
4.1	Average RMS values between experimental and simulated data . . .	77
4.2	Average ratio of the peak angular velocity between experimental and simulated data ($\omega_{max-sim}/\omega_{max-exp}$)	77
5.1	Model parameters	129
5.2	Sensitivity of simulation results to changes in model parameters . .	139

Chapter 1

Introduction

In this thesis, we evaluate the reliability and applicability of the threshold control theory (λ -model) with a subject-specific musculoskeletal model. Experimental and simulation studies show that threshold control theory performs well in the modeling of single joint movement. Then we extend the threshold control theory to the artificial human movement control technology, i.e., FES technique. Considering the lost functions of patients, the original threshold controller is modified. We further combine threshold control theory and CPG to achieve more complicated rhythmic movements, such as human walking. Our simulation results prove the reliability of this controller even with large feedback delay.

1.1 Background

For paralyzed patients, artificial human motor control such as functional electrical stimulation (FES) technique is expected to restore their lost functions. However, till now these technologies are only applied to prevent muscular atrophy but

not to restore the full function. This is due to the fact that the understanding of human motor control system is limited.

It is well known that computer modeling is very helpful in understanding control systems and developing intelligent artificial controllers. Firstly, modeling better reveals the relationship between the motor functions and the underlying neuromuscular structure, which can provide links between measurable changes in motor behavior and neuromuscular disorders. Secondly, it gives us ideas in the development of new control algorithms and advanced control devices, such as human-machine interfaces and robotics. Although the modeling of the human motor system is important, an ideal model of human motor control system is still under investigation due to the complexity of this system. Research in this area requires knowledge about neuroscience, biomechanics, control engineering, biomedical engineering and biological cybernetics. To build a reliable control system model, we should understand the structure of musculoskeletal system and construct the subject-specific model to predict the behaviors of the system.

Based on current understandings of human motor control system, there are two problems for constructing an artificial controller: 1) how to generate commands sequence to realize a desired task, 2) how to control the human body to realize these commands. Most of the proposed models of central nervous system (CNS) are too complex [2, 3] to implement them into hardware of artificial human motor control systems. On the contrary, simpler motor control strategies are questioned due to the lack of physiology basis. Therefore, the ultimate task of artificial human motor control is to develop and verify a physiology-based human motor control strategy and further apply this strategy to rehabilitation engineering.

1.2 Synopsis

The purpose of this Ph.D. study is to build a proper control strategy for artificial human motor control. In detail, we firstly develop a neuro-musculoskeletal model to predict human behavior and test the proposed controller. Considering the influence of inaccurate parameters to the simulation study, a novel method is proposed to estimate the critical parameters *in vivo* based on the musculoskeletal ultrasound and anthropometry. Its validity is then examined by two approaches: 1) compare the estimated parameter values with cadaver data collected from literatures [4–7]. 2) compare the subject-specific model predicting joint torques with experimental records.

In detail, we try to “learn” the control idea from the human central nervous system (CNS) to create new control methods to deal with the complexities of the musculoskeletal system, i.e., bio-mimetic controller. Based on our study, we found threshold control theory (λ -model) might be a good candidate. The threshold control theory is physiology-based model which can be employed for parametric control of voluntary movement. From the perspective of control engineering, the mechanism of threshold control theory suggests that limb movements can be controlled without solving the “inverse dynamics problem”.

However, till now the threshold control theory is a hypothesis and still under debate. Therefore, the first task of this study is to validate the threshold theory and its extensions through simulation study as well as experimental investigation. After threshold control theory is validated, we modify and implement the threshold control theory to FES technique for upper arm motor control and further for human walking with combination of central pattern generator (CPG).

1.2.1 Subject-specific musculoskeletal model

To provide insights in analyzing human movements, it is necessary to develop a subject-specific musculoskeletal model. Firstly, a musculoskeletal model is developed based on latest and most reliable theories we can find. Then, we identify the model parameters for individual subjects and evaluate the validation of subject-specific model by experimental study. To tackle the difficulty to measure muscle structure parameters in vivo, a novel method is proposed to estimate several critical parameters of elbow musculoskeletal model using the ultrasonography and anthropometry. Its validity is examined by comparing with reported cadaver data. Finally, the estimated parameters are applied into the musculoskeletal model to predict elbow joint torque. A comparison between experimental and simulation results suggests that the model with subject-specific parameters can predict the properties of the human motor system.

1.2.2 Verification and modification of threshold control theory

The threshold control theory assumes that the voluntary movements are produced by shifting the threshold (λ) of appropriate muscles. The theory has good computational properties as it does not need to solve the muscle torques required to move the system along a desired trajectory. However, it has been argued that the threshold control theory is not feasible for fast single-joint movements, e.g., it can not generate movement fast enough to match the experimental data. To refute this statement, several extensions have been proposed to improve the peak velocity of movement, but they have neither been tested adequately nor with subject-specific models. In the present study, a threshold controlled model for

the human elbow movement is developed with detailed musculoskeletal properties. The subject-specific musculoskeletal parameters are estimated by ultrasonography and anthropometry in vivo. To quantify performance, the movement features extracted from the simulation and experiment of the normal/fast elbow movements are compared. The results suggest that the threshold controller can ideally 1) generate the neural inputs, 2) reproduce corresponding muscle activation patterns, 3) drive the musculoskeletal system to realize desired movements even with feedback delays. Furthermore, two extensions are proposed and tested in this study. One extension sends the control signal intermittently instead of continuously. The other employs the feedback on the difference between the actual and desired velocities, instead of the feedback on the actual velocity. Further results suggest that the intermittent version can not improve the performance and may result in many noises. In contrast, the modification of feedback can significantly increase the peak velocity of the output movement and reduce the responding delay of the system, although this extension generates some noises to velocity profile too. In summary, this study shows that the single joint movement can be realized without solving the inverse dynamic problems. In another word, this movement can be achieved in a physiologically straightforward manner.

1.2.3 Study of threshold FES control system

Threshold control theory is based on the natural process of voluntary movement. It assumes that the voluntary movements are generated by shifting the thresholds (λ) of appropriate muscles. The dynamic thresholds depend on the static threshold and feedback of actual velocity. The threshold control theory has good control aspect, such as easy implementation. So we intend to apply it to FES technique to build a physiology-based controller. This idea is tested in our

study with an integrated musculoskeletal model. The simulation results suggest that the controller based on the threshold control theory alone can realize the task with small feedback delays. However, it is not capable to produce the movement fast enough to match the desired trajectory. Thus two extensions to improve the performance are proposed. Firstly, the feedback on actual movement velocity is replaced by the differences between the actual and desired velocities. Secondly, the feedback of joint angular acceleration is introduced to calculate the dynamic threshold. Simulation results suggest that such the extensions can 1) improve the movement speed; 2) reduce the response time; and 3) reduce influence of external perturbation and feedback delays.

After testing the applicability of the threshold FES controller for upper limb movement, we next study more complex motion control of human walking. Some researchers suggested that the rhythmic motor pattern for walk could be produced by the multiple threshold controllers [8]. However, their approach neglected the CPG, whose function had been clearly validated by many deafferentation experiments [9, 10]. We integrate the threshold control theory and CPG in a dynamic walking model. It is assumed that CPG activates the low level neural circuit (represented by threshold controller) before the movement initiation, and the threshold controller modulates the initiation signal based on the motion feedback and then generates the stimulation pattern for individual muscle. The proposed strategy is validated by simulation study. The results also suggest that the proposed controller is robust to various feedback delays and perturbations.

1.3 Contribution

The contributions of our study are summarized in the following aspects:

1) A novel approach has been developed to estimate the *in vivo* musculo-tendon parameters by ultrasonography. And a subject-specific musculoskeletal model has been built with these parameters.

2) The threshold control theory has been validated by simulation and experimental study. The simulated human motor control system model has been developed by applying the threshold controller to the subject-specific musculoskeletal model. To further improve the performance of threshold controller, two extensions have been evaluated. i.e., intermittent extension (the continuous control commands are replaced by the intermittent control commands [11]) and diff. extension (the feedback on the actual velocity is replaced by the feedback on the difference between the actual and desired velocities. [12]). It is found that diff. extension can reduce the responding time of the system and improve the peak velocity of the movement.

3) A novel FES control strategy for human upper limb movement has been proposed based on the verified threshold control theory. Based on our knowledge, it is the first time that the threshold control theory is employed in FES technique for multiple joints movement. Simulation results suggest that, i) the novel controller works with relatively simple structure, ii) the controller is robust to the changes of internal properties and the external environments.

4) Another novel FES control strategy for more complicated human walking has been developed by integrating the verified threshold control theory and the CPG theory. This strategy provides a new approach for rhythmic human motor control and also suggests the roles of CPG and reflex regulator in human motor control.

1.4 Organization of the thesis

The rest of the thesis is organized as follows:

In chapter 2, a comprehensive literature review of the human motor system, modeling of neuro-musculoskeletal system and motor control theories are given.

In chapter 3, a musculoskeletal model based on the latest theories that we can find is developed. We estimate the values of model parameters for individual subjects and validate the model by experimental study.

In chapter 4, a controller based on threshold control theory (λ -model) is developed for human upper limb motor system. Experimental and simulation results prove that the threshold controller is effective to generate single joint movements with proprioceptive feedback delays. Furthermore, two extensions which were proposed previously to improve the system response speed, are evaluated.

In chapter 5, the threshold control theory is employed to build a physiologically motivated FES controller. Simulation results suggest that the controller based on the threshold control theory alone can realize the task with small feedback delays. However, if we introduce the feedback of joint angular acceleration to calculate a dynamic threshold, the system can work well with larger feedback delays.

In chapter 6, the threshold control theory and central pattern generator (CPG) are integrated to develop a new FES controller for a dynamic walking model. The validation of the proposed controller is proved by simulation study. Comparing to the previous study of locomotion based on threshold control theory alone, the integration of CPG provides a natural walking rhythm. This work provides a possible explanation for the physiological roles of CPG and threshold controller in human walking as well.

Finally, conclusion and recommendations for further research are given in chapter 7.

Chapter 2

Literature Review

To provide insights in analyzing human movements and restore functions in paralyzed patients, it is necessary to understand the structure of motor system and then construct the artificial motor controller to simulate the function of the natural motor control center. There are three main parts in the motor system: central nervous system (CNS), sensory feedback and skeletal-muscle system. To make an analogy to a control system, they correspond respectively to controller, sensor and actuator in a close-loop control system.

The CNS is the part of the nervous system that serves as the main “processing center” for the entire nervous system, and controls all the movements of our body. The CNS consists of the brain and spinal cord. Either consciously or unconsciously, CNS functions to receive and interpret signals from the peripheral nervous system and also control its behavior. The details of CNS is described in section 2.1.

The human natural sensors related to movements can be classified as proprioceptor and exteroceptor. Proprioceptor includes the vestibular system and mechanoreceptor located in the muscles, tendons, ligament and skeletal joints.

The proprioceptor collects information about the position and movement status of the limbs and send back this information to the CNS as well [13]. For example, proprioceptors in joint capsules and ligaments detect joint angle and angular velocity. While in muscles, they collect the information of muscle length, change of length and also the muscle tension (refer to section 2.2.3) [1]. On the other hand, the exteroceptor includes cutaneous receptors and visual system, that provides information about the our location and movements of body segments with respect to the environment. It is important for the maintenance of posture and the prediction of movement trajectory.

The lowest level of the human motor control system is musculoskeletal system, which is the executant of descending commands from CNS. Modeling of the musculoskeletal system is a very active research area. In the section 2.2, a brief survey is presented.

This chapter is organized as follows: Firstly, the physiology basis of central nervous system is presented in section 2.1. Next the properties of musculoskeletal system, especially the characteristics of skeletal muscle are introduced in section 2.2. After presenting the physiology knowledge of human motor system, the modeling for the neuro-musculoskeletal system is introduced in section 2.3. To provide readers a better understanding of the modeling mechanism, an simple example is presented in this section as well. Finally, theories and technologies of motor control, in particular, FES control and threshold control theory, are presented in section 2.4.

2.1 Central nervous system

Most artificial motor controllers intend to replace the functions of CNS for paralyzed patients. Thus it is essential to understand the physiology of CNS.

The CNS of the motor control is composed of the spinal cord and the higher motor centers in the brain, e.g., the associative cortex, the motor cortex, the cerebellum, the basal ganglia and the brainstem. Generally speaking, the higher centers mainly have two functions. 1) they determine the goal and overall direction of movements; 2) they provide motor commands for the spinal cord. The simple hierarchical diagram about the mechanism of CNS is shown in Figure 2.1. Comparing with the higher motor center, the spinal cord, which is comprised of neural integration unites, serves as a main pathway from higher center to peripheral nerves and generates some simple movements by itself [14]. Within CNS, the spinal cord is the most extensively studied motor centers. Thus a brief discussion about it will be given in the rest part of this section.

Figure 2.1: The hierarchical diagram of the CNS mechanism.

2.1.1 Introduction of spinal cord

Spinal cord is one of the most important part of human body. Its function mainly lies in two aspects [15, 16]: 1) the spinal cord channels the communication between the brain and the peripheral nervous system. For example, it descends the command from the brain to cause the muscle contractions, and also feedbacks the sensory information from the body organs or external environment to the brain. 2) the spinal cord coordinates various reflexes [1]. Reflex is our body response to the dangerous stimuli, for example, touching the extremely hot or cold objects. In such circumstances, the speed at which the information travels between the peripheral nervous system and the brain is not fast enough to avoid the damage of body, Thus the spinal cord will organize neural integration unites to trig the reflex action.

It is crucial for rehabilitation engineer to deeply understand the function of spinal cord. Many theories and models has been built to describe and replicate the behavior of spinal cord and affiliated organs [3, 17]. In this study, I intend to mimic the functions of spinal cord to realize artificial motor control as well.

2.1.2 Neuronal network of spinal cord

To serve many different functions, spinal cord has complex neuronal networks comprised of various types of neurons. In this section, to avoid the cumbersome, only the neurons of spinal cord related to our work are presented, which mainly consist of motor neurons (or motor neuron) and interneurons. The motor neurons can be divided into two types: α neurons and γ neurons. α motor neurons innervate extrafusal muscle fibers located throughout the muscle. γ motor neurons innervate intrafusal muscle fibers within the muscle spindle [3].

Interneurons are the multipolar neurons which connect afferent neurons and efferent neurons [10]. There are mainly two functions of interneurons: 1) they connect sensories and motor neurons; 2) they constitute networks to generate complicated patterns (e.g., rhythm generator). There are three groups of inhibitory interneurons (1a, 1b and Renshaw cells) to coordinate muscle action around a joint. Their functions are modeled as inhibitory gains in our study.

To illustrate the function of neuronal network, we take the stretch reflex as an example. Stretch reflex is the process that the continuous force is generated by non-contracting muscle to oppose stretching [18]. When the muscle is stretched, the change of muscle length is detected by the sensor located in the muscle spindle. Then the intensity of sensory feedback is regulated by γ motor neurons. In detail, the activation of γ motor neuron will cause the contraction of intrafusal muscle fibers, thus the threshold required to activate the spindle sensor is decreased. Finally the feedback signal is transmitted to spinal cord. The neuron network of spinal cord will coordinate various muscles to resist further stretching by activating the α motor neurons.

Functionally, the neuronal network of spinal cord includes various modules (e.g. CPG and regulator). Because CPG and regulator are modeled in chapter 6, only the brief introductions of them are given in following sections.

Central pattern generator

Based on the experiments of Graham-Brown in 1911, it was found that the rhythmic pattern can be produced by the spinal cord without the descending commands from the higher center [9, 19]. The module for achieving this function is called central pattern generator (CPG), which is widely distributed in spinal cord. For example, CPG for locomotion is located throughout the lower thoracic and

lumbar regions of the spinal cord [20]. Generally speaking, CPG can construct motor pattern to generating rhythmic movement such as locomotion and cycling, in the absence of both sensory and descending input.

Regulator

From the perspective of neuroscience, CPG is connected with muscles through a complex neural circuit (*regulator*). This circuit contains different motor neurons and interneurons. It is noted that neurons comprising this neural circuit are also the main components of neural network for achieving spinal reflex [21]. Thus we assume that the *regulator* not only modulates the signal from the CPG but also processes the sensory feedbacks to realize simple movements. It is still unclear about the mechanism of the *regulator*, i.e., how it coordinates different sensory feedbacks and descends control signals to construct different control loops. However, some efforts had been done to explain the coordination and interaction mechanism amongst the neurons of *regulator* [2, 3, 21, 22].

2.2 Musculoskeletal system and muscle properties

The musculoskeletal system is a complex system comprising of bones, soft connective tissues and muscles, to generate human body movements. In these organs, skeletal muscle is our interest since it executes the descending motor neuron commands to produce human body movement. Skeletal muscles are attached to the bones via tendons, and they move bones by active contracting and shortening due to the descending commands. It is noted that skeletal muscles can not achieve

the active lengthening. In order to realize back-and-forth movement, typically, a set of muscles (agonists) are activated as the primary activators of motion, while the opposite set (antagonists) counteract the agonists and oppose the motion.

2.2.1 Physiological properties of muscle

Muscle contraction

Generally speaking, muscle contractions can be classified as two types [23,24]: 1) static or isometric contractions, that refer to force production without changes in muscle length; 2) dynamic contractions, that refer to force generation with muscle length change. The dynamic muscle contraction can be subdivided as isotonic (muscle force remains constant), isokinetic (contraction velocity remains constant) and isoinertial (contraction acceleration remains constant).

Natural muscle contraction is caused by the action potential generated in CNS (twitch response in excitation-contraction sequence). Contraction duration depends on the type of involved muscle and the size of muscle fibers, but not on the duration of the stimulus [25]. Normally, an initial delay can be observed at the start of contraction, which is due to the conduction time of the descending commands as well as the time for the release of the calcium ions. It is noted that the number of muscle fibers involved in contraction determines the maximum force production of muscle. Because this number can not be counted *in vivo*, the cross-sectional area of muscle is typically used to estimate the maximum muscle force [26]. The muscle contraction can also be caused by external electrical stimulation. The muscle contraction/activation under external stimulation is determined by muscle fatigue properties, pulse width and frequency of stimulation [24].

Figure 2.2: Sketch map of tetanus. Increase of stimulation frequency leads to double twitch and finally yields a steady force output (Adapted from [24]).

It is noted that maximum contraction level is determined by the tetanic frequency [18]. When a high frequency stimulation is applied to muscle, the muscle unit will be stimulated again before the first twitch has died away. Therefore, the second twitch will lead to a stronger contraction because the muscle unit has not been completely inhibited after the first twitch. If the frequency of stimulation is increased, the force output inclines to a steady force level, which is the maximum force that can be produced by this motor unit (Fig. 2.2). The relevant frequency is termed tetanic frequency. i.e., the stimulation with frequency higher than tetanic frequency can not yield any more increases in force.

Fatigue

It is known that the muscle can not maintain the maximum force production for a long period due to the phenomenon termed fatigue. Fatigue may occur due to the following reasons [27]:

- 1) The depletion of nutrients in the muscle fibers. When the muscle force increases, less blood reaches the working muscle as the wall of arteries is compressed

and the blood flow is occluded. Thus the muscle had to work on a greater amount of glycolytic metabolism with concurrent fatigue.

2) The depletion of ACh in the nervous system, that less ions can be used to produce the action potentials.

Since the fatigued muscle is incapable to continue working even if we change the type of activity, the CNS may coordinate other muscles to compensate for the function of the fatigued muscle.

2.2.2 Mechanical properties of muscles

The mechanical properties of muscle is important for muscle modeling, most of the basic properties of muscle were postulated by A.V. Hill and his colleagues [28]. The introduction in this section is also mainly based on their theory.

Force-length relationship

The muscle force-length relationship is the relationship between the length of the fiber and the resulting force at that length. This relationship is studied because the tension developed during muscle contraction highly depends on muscle length. Since the muscle tension includes the active and passive components, this relationship comprises of active force-length relationship and passive force-length relationship [29].

Active force-length relationship describes the characteristics of stimulated muscle fibers. Maximum force is produced at the muscle optimal length, and then drops off as the muscle either shortens or lengthens. Passive force-length relationship is derived from passive properties of the muscle. When the muscle (no electrical stimulation) is stretched, the passive force can be observed and the rate

Figure 2.3: Force-length relationship in fusiform muscle, where l_0 is the optimal muscle length.(Adapted from [1])

of force increase is linear to the applied stress. To sum up, the total muscle force should be the combined effect of the active and passive components, as shown in Fig. 2.3.

Force-velocity properties

The force-velocity relationship describes the phenomenon that the muscle force development decreases as the velocity of the movement increases. A typical curve of force-velocity properties is shown in Fig. 2.4. It is noted that the force produced for eccentric motions (negative velocity in Fig. 2.4) can reach a higher value than the isometric force. This fact is due to following two reasons: 1) Stronger force is required to break the cross bridges than to hold them at their isometric state; 2) Muscle force must overcome latent viscous friction generated during the shortening stage [18].

Figure 2.4: Force-velocity relationship (Adapted from [1]).

2.2.3 Receptors of muscles

Receptors are the kind of nerve cells that detect the movement status and feedback the information to CNS [30]. There are two important muscle receptors in the motor control procedure, i.e., muscle spindle and golgi tendon organ. The details of them will be briefly introduced as follows.

Muscle spindle

Muscle spindles are located in parallel with the regular muscle fibers, which primarily detect changes in fiber length and velocity. The muscle spindles are composed of muscle fibers in terms of intrafusal fibers, while the regular muscle fibers are termed extrafusal fibers. The receptors of muscle spindle detect the length and velocity information of intrafusal fibers and send back to CNS. It is noted that the intrafusal fibers are innervated by the motor neurons termed fusimotor neurons. When the fusimotor neurons is activated, it will cause the contraction of the intrafusal muscle fibers and then elongate the non-contractile portion of spindle.

Thereby, the muscle spindle receptors will be more sensitive to stress. In the modeling, a feedback gain should be given to presented this sensitivity modification [2].

Golgi Tendon Organs

Golgi Tendon Organs (GTOs) are the proprioceptive sensory receptor organ that are sensitive to muscle tension. In detail, GTOs detect the changes of muscle forces, both in the form of active forces resulting from muscle contraction and passive forces developed by the muscle stretch.

2.3 Modeling of neuromusculoskeletal system

Modeling of human motor system can provide us deeper understanding for the mechanism of the human motor system and is also the prerequisite for the artificial human motor control such as FES. Like other plants in control engineering, the modeling of human motor system also includes the modeling of joints, actuators and sensors. But the general analytical tools used for the modeling of mechanical plants can not be simply extended to the modeling of bio-mechanical systems, otherwise the results produced by the model will present sharp discrepancy to reality.

Generally speaking, the problem of motor control is how to generate a sequence of commands for solving a previously specified task and how to control the human body to realize these commands. The tasks of human limb motions are called trajectories and consist of a sequence of positions, velocities, and accelerations of any part of the system (e.g., hand, foot, etc.). If the limbs is modeled as rigid body links with muscles, tendons, ligaments, and soft tissues, we can solve the motion

task by setting the desired joint angle, angular velocity, acceleration and stiffness. Noted that stiffness is defined as the resistance of muscle to deformation. Thus, the necessary muscle forces can be anticipated by using laws of mechanics to follow the given trajectory.

To build a model of human limbs, 1) the first step is to determine the inertial properties of a limb segment such as mass and the inertia tensor. The inertia tensor determines the inertial properties of the body when rotating. The mass describes its inertia when motion status is changed. 2) The second issue in the modeling is to describe joint structures, which determine the degrees of freedom (DOF) and motion range of movement. Typically, a limb joint can be modeled as a pure pin or ball joint. However, some joints are more complicated such as double mechanical joints (e.g., ankle joint). 3) After deciding the inertial properties and joint structures, the next issue is to anticipate the internal muscle forces. It is necessary to build a model in order to describe the excitation-contraction properties and mechanic characteristics of muscles. 4) Finally, the motor sensors should be modeled, thus the controller can integrate the feedback information and preliminary motor commands to generate commands to adapt environmental changes.

2.3.1 Modeling of neural circuits

There are many models are proposed to describe the structure and function of neural circuits, for example, Huxley-Hodgkin models [31]. Here an example for antagonist muscle is given, i.e., α - γ model developed by Lan et. al. [2]. Refer to the signal flowchart shown in Fig. 2.5, Renshaw cell plays as an inhibitory role in the activation; the spindle acts as feedback regulation of the joint dynamics; and the γ neuron is used to adjust the feedback from spindle.

Figure 2.5: The signal flowchart of model of the neural circuits. Two inputs are sent to the spinal cord, i.e., the α descending commands (N) and γ descending command (γ). The descending excitation signals are transformed into muscle activation A to produce the movement. The length and velocity of muscle contraction is fed back through spindle to regulate the activities of motor neurons. This regulation includes muscle stretch reflex (gain s), reciprocal inhibition (gain r) to the opposing muscle, and recurrent inhibition from the Renshaw cells (gain g).

The α -motor neurons in the spinal cord are the main processing units that

combine excitatory and inhibitory synapses of all reflexes and descending commands to generate muscle activation. The dynamics of α -motor neurons can be briefly described as following formulas

$$\begin{aligned}\frac{dc_f(t)}{dt} &= -\frac{c_f(t)}{\tau_{N_f}} + \frac{N_f(t)}{\tau_{N_f}}, \quad 0 \leq N_f(t) \leq 1 \\ \frac{dc_e(t)}{dt} &= -\frac{c_e(t)}{\tau_{N_e}} + \frac{N_e(t)}{\tau_{N_e}}, \quad 0 \leq N_e(t) \leq 1\end{aligned}\tag{2.1}$$

where $c(t)$ represents the synaptic potentials. $N(t)$ represents the descending command. τ_N is the time constant of activation. The subscripts f and e represent flexor and extensor muscles, respectively. Noted that the formula 2.1 suggests that there exist the saturation ranges during the response of motor neurons to the descending commands. This non-linear property of motor neurons provides the fundamental for the threshold control theory, which will be introduced in section 2.4.2.

Next, the neuron outputs $u(t)$ are determined by $c(t)$ [32]. Their relationship is described by

$$\begin{aligned}u_f(t) &= \frac{c_f(t)}{1 + c_f(t)g_f}(1 + s_f v_f - r_f v_e) \\ u_e(t) &= \frac{c_e(t)}{1 + c_e(t)g_e}(1 + s_e v_e - r_e v_f)\end{aligned}\tag{2.2}$$

which are the sum of all excitatory for flexor muscle and for extensor muscle, where s represents the stretch reflex gain; r is the reciprocal inhibition gain; g is Renshaw cell gain and $v(t)$ is proportional to Ia afferent discharge frequencies of spindles, which represents the muscle length and velocity feedback from spindles. The neuron outputs further determine the muscle activation, which is discussed in section 2.3.2.

2.3.2 Muscle model

Generally speaking, there are three classes of muscle models in terms of the level of muscle structure: 1) microscopic models, which can be further divided into the “conventional” (Huxley-type [33, 34]) and “unconventional” cross-bridge models; 2) fiber models; 3) macroscopic (whole muscle) models, which can be further divided into the Hill-type model [35], viscoelastic model and system model [36, 37].

In these models, Huxley-type microscopic model and Hill-type macroscopic model had been widely recognized. In detail, the former offers superior credibility while the latter is much more tractable. Due to the complexity of the microscopic model, the Hill-type model is one of the earliest and perhaps most popularly employed model.

The Hill-type model, shown in Fig. 2.6, is composed of three elements [23]: the contractile element (CE) that models the active force, and a parallel-elastic element (PE). CE and PE operates parallel to generate muscle force (F^M), i.e., $F^M = F^{CE} + F^{PE}$. The series-elastic element (SE) represents the combined tendon and aponeurosis. The muscle force is transferred to musculo-tendon force F^T by the influence of SE, if the angle between the SE and muscle (pennation angle) is small enough, $F^M \approx F^T$. In the perspective of mechanical engineering, CE represents muscle’s force-length-velocity property, while SE and PE represent muscle’s active stiffness and passive stiffness respectively. In this thesis, active stiffness is defined as the resistance to active contraction and passive stiffness is defined as the resistance to elongation. The properties of the three elements are actually defined in terms of force-length properties and force-velocity properties in the muscle model (refer to section 2.2.2).

Figure 2.6: Hill's three elements mechanical model.

2.4 Motor control

Motor control is a very complex task dealing with a large scale, redundant, time-varying, dynamically non-determined, nonlinear system. The ultimate objective of motor control is to design a controller to mimic the function of CNS (central neuron system) for generating locomotion. Although this is a challenging task, it is worth studying for both biomedical and engineering purposes. Firstly, it can provide a better understanding of the function of CNS so that medical doctors may be able to treat diseases affecting posture and movement control more effectively. Secondly, new motor control strategy can be extended to artificial human control system such as FES by imitating the mechanism of CNS.

2.4.1 Problems in motor control

As mentioned in section 2.3, the task of motor control is to determine proper motor commands for realizing desired trajectory under variable environments. It is required to analyze the dynamics of motion. There are two methods for dynamic analysis, 1) determine the trajectories and laws of motion from the desired torques and forces (Forward dynamics). 2) determine the force and torques based on

desired laws of motion and trajectories (Inverse dynamics). The main problem of motor control lies in the computational complexity and redundancy.

The concept of redundancy means the number of possible inputs is larger than the required minimum number of the inputs. The redundancy is an important feature in biological systems. It is useful as the flexibility of the body movement is increased, but it also poses the redundancy problem, i.e., there are more than one proper approach to position the extreme of limb at an endpoint. To take a proper solution among the possible approaches that achieve the movement target, two strategies are employed in earlier attempts. Strategy 1 is to reduce the problem to a mapping problem by applying a non-redundant motion frame, for example, a non-redundant arm for robotic control [38]. This mapping problem can be solved by a feed forward controller, for example, an artificial neural network. Strategy 2 is to introduce an additional mechanism to explicitly deal with the redundancy problem [39].

The advantage of forward dynamics lies in the speed of computation and also avoidance of the redundancy problem. However, the forward dynamics require that the movements are completely predictable, which is almost impossible for human motor control: Firstly, it is hard to predict the change in the influence of environments. Secondly, it is hard to predict the movement resulted from the status change in the rest of body. Therefore, the analysis with forward dynamics is normally only applicable to open chain structures such as a swinging leg, but not applicable to closed chain structures such as walking leg. The advantage of inverse dynamics lies in its accuracy and robustness. The difficulties of inverse dynamics come from 1) errors generated through numerical computation on noisy input data and 2) uncertainties of solutions due to the redundancy of musculoskeletal system.

Since both forward dynamics and inverse dynamics have their limitations, it may be a good approach to combine these two strategies to control limb movement. For example, considering the lack of predictability of forward dynamics, we can replace some formulas of forward dynamics by hypothetical system parameters. Then these parameters will be updated based on the feedback of the motion situations [40].

2.4.2 Threshold control theory (λ -model)

Though researchers only started to comprehend the nature of human motor control and how the nervous system selects a specific set of muscles to produce a desired goal-directed movement, some hypotheses were proposed over the past decades [15, 41, 42]. In these hypotheses, the threshold control theory is one of the most credible candidates. It suggests that voluntary movements are generated by shifting muscle length thresholds (λ), at which the activity of muscle is initiated [43]. Many studies show that the threshold controller is feasible to control human limb movements by variable speeds and even large proprioceptive delays will not impair the performance [11, 44–46]. It can be said that the threshold control theory is a physiologically well established form of parametric control for voluntary motor actions.

On the contrary, some researchers argued that the threshold controller could not control limb movements by simply shifting thresholds. They suggest that human motor controller should directly involve the neural control levels in EMG-force programming and specification, e.g. internal model theory [47, 48]. In view of system performances, they claim that the threshold control model is only efficient in slow movements and postural control, but not feasible for fast movements [49–53].

Though the models depending on EMG-force programming and specification are also supported by some experimental evidences [47], they may be not applicable to the rehabilitation engineering. The controllers of EMG-force models are more complex than the threshold controller since they need dictate the movement details in terms of EMG signals, movement trajectories and muscle forces. This computation complexity induces the difficulty in the implementation into rehabilitation technology, e.g. FES. On the contrary, the threshold control theory provides a simple but elegant control strategy, e.g. it suggests that the brain has the capacity to specify global factors or parameters (like λ) to pre-determine the threshold of muscle contraction. From the viewpoint of control engineer, the mechanism of the threshold control theory shows that limb movements can be adequately controlled without solving the “inverse dynamics problem”. In other words, the threshold controller can easily achieve “forward control” for human movement and then largely reducing the time for formulating control commands.

The original version of the threshold control model produces control signals only through the representation of the joint angle to muscle length relationship. Two extensions were published in literatures over the last 20 years to improve the performance, i.e., i) a co-contraction command was added to increase stiffness to produce the fast movement toward the desired trajectory; ii) the feedback of contraction velocity was added to reduce the oscillation in the endpoint [54–56].

2.4.3 Control strategies of FES

Functional electrical stimulation (FES) is a widespread method to study the function of the nervous system and also a technique to restore the lost function due to the following disease or injury. Many people with neurological disorders

are benefited from FES-assisted locomotion [57]. In order to restore useful movements to a particular patient, it is necessary to design a control scheme to insure the safety and validity before applying the FES system to the patient. However, building an accurate and stable FES controller is very difficult because the musculoskeletal system with electrical stimulation has strong nonlinearity, time-varying and large latency [58]. Furthermore, a good controller must also compensate the influences caused by fatigue [59] and solve ill-posed problems (redundancy). From the point of view of the system response, a well-designed controller must satisfy two requirements: 1) The system must be globally stable; 2) The output trajectory must follow the designed trajectory with ease.

Many FES control strategies derived from robotic engineering or biological sensorimotor control have been proposed in the literature. Most of the them can be classified into the following categories: open-loop, close-loop, hybrid controllers and rule-based controllers. Stimulation patterns are generated by look-up tables [60, 61] or precise mathematical musculoskeletal models of the controlled limb. For example, the proportional-integral-derivative (PID) control, [62–64], model reference control [65], model predictive control [66], adaptive control [67–70], fuzzy logic control [3, 68, 71, 72], iterative learning control [73], H-infinity robust control [74], sliding mode control [75, 76], data-driven control [77], artificial neural network (ANN) control [78–83], and so on.

Furthermore, some researchers also tried to mimic the strategy employed by the central nervous system (CNS) to create new control methods to deal with the complexity of musculoskeletal systems, such as bio-mimetic control of FES reaching [84], feedback error learning control for the palmar/dorsi-flexion movement of wrist [85], neural control with central pattern generator (CPG) for locomotion[86].

At clinical sites, the open-loop and rule-based control scheme is most widely used control strategy because of its simplicity. However, these controllers need a

complex rule scheme to adapt to the conditions of individual patients. Or they need initial and periodical adjustments in stimulation patterns to compensate the external loads and muscle fatigue. The establishment of rule scheme and adjustment takes a great deal of time and impose the heavy burden on both patients and medical doctors. On the contrary, the closed-loop controllers with appropriate sensory feedback are superior to open-loop controllers to eliminate the effects of external perturbation and maintain system stability [62, 64]. However, the tracking error increases as the desired movement speed increases. This is because the response latency of the musculoskeletal system and feedback delay will diminish the ability of close-loop controller to produce stable outcome. At worst the oscillatory occurs as a result of large time lag when the controller intends to regulate stimulus/excitation after errors are detected. The hybrid controllers are developed to incorporate advantages of these controllers. It is expected that the open-loop controller can realize the fast movement without delay, whereas the closed-loop controller can prevent the destabilizing effect caused by perturbation and can adjust the system output to precisely follow the desired trajectory. However, the initial adjustment is still needed for most hybrid controllers.

To sum up, an engineering controller might provide good performance but can not replace the function of spinal cord to control FES system completely. On the other hand, the bio-mimetic controllers are always too complex to realize in hardware if they try to completely imitate the structure of CNS. Furthermore, engineering and bio-mimetic controllers are normally dependant on accurate information provided by multi-mode implanted sensor.

Though the engineering and bio-mimetic controllers both have pros and cons, the bio-mimetic controller attracts more attention. This is because it can provide novel ideas for control technology and may answer the question of how the CNS

controls numerous muscles to maintain a stable body posture or to produce multi-joint movements. If we can develop a reliable bio-mimetic controller with simple structure and few sensories, it will be a promising control strategy for FES system.

Chapter 3

Development of Subject-specific Musculoskeletal Model

3.1 Introduction

Musculoskeletal models are widely used to simulate the muscle force when analyzing human movement [23, 87]. One of the main challenges in modeling is to accurately estimate the muscletendon parameters on subject-specific basis. The underlying muscle contraction and dynamics information can only be derived from appropriate modeling. The sensitivity and validation studies reveal that the simulation results are significantly affected by the accuracy of muscletendon parameter values [88, 89].

In previous simulation studies, most researchers simply adopted reported cadaver data to predict muscle force and torque [90]. The modeling of musculoskeletal system based on cadavers has limited the potential to predict human movements. For example, after comparing the fibre length and the pennation angle of medial

and lateral gastrocnemius in cadaver and live subjects via ultrasonography, Martin et al. [91] found that architectural characteristics of cadaver muscle differ from both relaxed and contracted *in vivo* muscle. Therefore, errors will be accumulated if the cadaver data is used in modeling muscle functions. Furthermore, even for the same person, the properties of musculotendon systems also change over age [92]. Some investigators have used medical imaging techniques to estimate muscle structure parameters *in vivo*, such as ultrasound [93], computerized tomography (CT) [94] and Magnetic Resonance Imaging (MRI) [95]. Considering the disadvantage of MRI or CT, such as high cost and radiation exposure, ultrasonography is a better choice for researchers, as it is more convenient for repeated measurements compared to the other techniques. The disadvantage of ultrasonography lies in the relatively lower image resolution compared with other medical imaging modalities, e.g. MRI and CT. Previous measurements of musculotendon parameters using ultrasound were mainly used to evaluate the muscle function [96]. Few of them were utilized to estimate musculotendon parameters for modeling of musculoskeletal system.

To our knowledge, this is the first time to develop a subject-specific musculoskeletal model for a live person by the ultrasound imaging technique. In detail, the following parameters are measured by ultrasonography: the peak isometric muscle force, the optimal muscle fascicle length and the attachment points of the musculotendon. However, due to low resolution of ultrasound images, some parameters are not clearly observed from the ultrasound image. To circumvent this problem, the unmeasured parameters are calculated by combining the cadaver data and the available parameters. Using these parameters, a musculoskeletal model is built and driven by a physiology-based controller to predict elbow movement. Simulation results are compared with recorded experimental joint torque to evaluate the model performance.

The remaining part of this chapter is organized as follows: The musculoskeletal model of human upper limb is introduced in section 3.2. The estimation of model parameters is addressed in section 3.3. The experimental setup and data acquisition are presented in section 3.4. The comparison of simulation results and experiment data are shown in section 3.5. Discussions and conclusions are given in section 3.6.

3.2 Musculoskeletal system model

In this section, the model describing major properties of muscle and segmental dynamics is given. The musculoskeletal model of the human upper limb is presented as three segments connected by two hinges joints (glenohumeral joint and the elbow joint, Fig. 3.1). To reproduce the experimental elbow flexion and extension, it is assumed that the elbow bends have only horizontal movements and are actuated by five lumped muscles: first monoarticular elbow flexor (Biceps long head), second monoarticular elbow flexor (Brachialis), a monoarticular elbow extensor (Triceps Lateral head and Medial head), a biarticular elbow flexor (Biceps short head), and a biarticular elbow extensor (Triceps long head) (Fig. 3.1). The path of a musculo-tendon complex is represented by a straight line joining the centroids of the muscle attachment sites.

Figure 3.1: The geometric relations of the elbow. To simplify, a hinge joint with no wrap-around insertions of muscles is used to describe the joint geometry. 5 antagonist muscles are included. The condition of external loading is simulated by the spring and damping elements attached at the endpoint. θ is the elbow joint angle, and counterclockwise rotation is defined as positive. The range of motion of θ is from 0° (Extension) to 140° (Flexion) (Adapted from Luttgens and Hamilton [97]). The should joint angle θ_{sh} is fixed to 120° .

For each muscle, we model the dependence of muscle force on the muscle fascicle length, muscle contraction velocity and muscle activation, as shown in Fig. 3.2. In detail, the muscles are modeled as modified Hill-type unit consisting of a contractile element (CE), a parallel elastic element (PE), and a series elastic element (SE). The SE is not involved in this study because it is negligible for the operating conditions in our model [23]. Calcium dynamics describes how muscle excitation (net neural drive) leads to muscle activation, which is modeled as a first-order process [2, 23, 87]. The delay between muscle excitation and activation (or the development of muscle torque) is mainly due to the calcium(Ca)-dependent

Figure 3.2: The sketch map of musculoskeletal model. It shows the procedure from spinal cord's descending commands to the final joint angle changes.

processes [98]. Furthermore, the tendon is represented as an elastic element. It is assumed that the tendon force varies linearly with length changes when tendon is stretched from its slack length. The burst of muscle force results in the joint angle changes due to joint dynamics.

3.2.1 Activation dynamics

Since muscles can not be activated or relaxed instantaneously, the delay between muscle excitation $E(t)$ and the muscle activation $A(t)$ can be described as a first-order function based on the Hill-type model, i.e.,

$$\dot{A}(t) = \frac{(E(t))^2 - E(t)A(t)}{\tau_{rise}} + \frac{E(t) - A(t)}{\tau_{fall}} \quad (3.1)$$

where rise time τ_{rise} and relaxation time τ_{fall} are time constants for the calcium dynamics of muscles [87].

3.2.2 Contraction dynamics

The muscle model is based on the musculotendon actuator described in [23]. To well describe the physiological structure, we use a modified Hill-type formulation by Brown et al., 1996 [99], 2000 [100] for the force development of the muscle. That is, the muscle force is described as the sum of force produced by the CE and the force produced by the PE:

$$F^M = F^{PE} + F^{CE} \quad (3.2)$$

The muscle active force is determined by,

$$F^{CE} = F_{max} FV(\tilde{V}^M) FL(\tilde{L}^M) A(t) \quad (3.3)$$

where F^{CE} represents the muscle active contractile force, $\tilde{V}^M$ represents the normalized muscle contraction velocity to the maximum shortening velocity of the muscle, $\tilde{L}^M$ is the normalized muscle fascicle length to the optimal muscle fiber length, FV is the force velocity factor, FL is the force length factor, $A(t)$ is the muscle activation, and F_{max} is the maximal isometric active force. It is assumed that the values of F_{max} of flexor and extensor are same.

FV is approximated by an exponential function [90],

$$FV = \frac{a}{1 + e^{b(\tilde{V}^M - c)}} \quad (3.4)$$

where a , b , c are proper constants.

FL is modeled as a polynomial curve [101].

$$FL = d(\tilde{L}^M)^2 - 2d\tilde{L}^M + d + 1 \quad (3.5)$$

where d is a scaling factor, whose value is determined by the particular range “width” of normalized muscle fascicle length. A muscle generates a positive force when the normalized length exceeds this range. Therefore, FL has a positive value.

The parallel elastic element is modeled as a two parallel spring system [99,100]. The total force produced by PE can be presented into two components: F^{PE1} , represents the force produced by the non-linear spring to resist stretch in the passive muscle; F^{PE2} , represents the force produced by the non-linear spring to resist compression during active contraction at short lengths, i.e.,

$$F^{PE} = F^{PE1} + A(t)F^{PE2} \quad (3.6)$$

The values of F^{PE1} and F^{PE2} are given as,

$$F^{PE1} = \{c^{PE1}k^{PE1} \ln\{\exp[(\frac{\tilde{L}^M}{\tilde{L}_{max}^M} - \frac{L^{PE1}}{k^{PE1}})] + 1\} + \eta V\}F_{max}, \quad F^{PE1} \geq 0 \quad (3.7)$$

and

$$F^{PE2} = \{c^{PE2}(\exp(k^{PE2}(\tilde{L}^M - L^{PE2})) - 1)\}F_{max}, \quad F^{PE2} \leq 0 \quad (3.8)$$

where $c^{PE1}, c^{PE2}, k^{PE1}, k^{PE2}, L^{PE1}, L^{PE2}$ and η are the constants.

3.2.3 Tendon compliance

The tendon is modeled as a linear spring with a stiffness of k^T [90]. The value of k^T is collected from literatures [90,102,103]. The tendon length is determined as:

$$L^T = \frac{F^T}{k^T} + L_s^T \quad (3.9)$$

where L^T is the length of tendon, $F^T = F^M * \cos \alpha_p$ is the tendon force, which is influenced by the pennation angle (α_p), L_s^T is the tendon slack length. It is defined as the elongation length, beyond which the tendon starts to develop force.

Tendon slack length is determined as in [104],

$$L_s^T = L_{max}^{MT} - c_s^T L_o^M \quad (3.10)$$

where L_{max}^{MT} represents the maximally elongated musculotendon length, c_s^T is the proportion generalized from anatomical data [5, 105] and L_o^M is muscle optimal physiological length. Then, the muscle fibre length L^F is calculated by subtracting tendon length L^T from L^{MT} , and the pennation angle (α_p) is taken into account:

$$L^F = \frac{(L^{MT} - L^T)}{\cos \alpha_p} \quad (3.11)$$

Note that the effects of pennation on muscle actuators are only significant when muscle fibers are highly pennated [23]. The human elbow flexor and extensor muscles all have the small pennation angles ($< 30^\circ$) [5, 105, 106]. Therefore, we just simply assume the pennation angle equal to zero.

Furthermore, the muscle contraction velocity V^M is calculated from the dynamic properties of musculotendon actuator, which are expressed by a first-order differential equation based on Zajac's work [23]:

$$\dot{F}^T = \dot{F}^M = k^T(V^{MT} - V^M) \Rightarrow V^M = V^{MT} - \frac{\dot{F}^M}{k^T} \quad (3.12)$$

3.2.4 Anatomical arrangement

Fig. 3.1 shows the anatomical arrangement of flexors and extensors at the elbow joint. Therefore, the moment arms of muscles can be calculated by the geometrical relationship as shown in Fig. 3.3.

For the monoarticular flexor, extensor and brachialis, the musculotendon lengths are determined as

$$\begin{aligned} L_{mf}^{MT} &= \sqrt{(L_{mf}^{ua})^2 + (L_{mf}^{fa})^2 + 2L_{mf}^{ua}L_{mf}^{fa}\cos\theta} \\ L_{me}^{MT} &= \sqrt{(L_{me}^{ua})^2 + (L_{me}^{fa})^2 - 2L_{me}^{ua}L_{me}^{fa}\cos\theta} \\ L_{bra}^{MT} &= \sqrt{(L_{bra}^{ua})^2 + (L_{bra}^{fa})^2 + 2L_{bra}^{ua}L_{bra}^{fa}\cos\theta} \end{aligned} \quad (3.13)$$

3.3.a: geometrical relationship of monoarticular flexor and extensor

3.3.b: geometrical relationship of biarticular flexor and extensor

Figure 3.3: Geometrical relationship of elbow muscles.

and the moment arms are,

$$\begin{aligned} h_{mf} &= \frac{L_{mf}^{ua} L_{mf}^{fa} \sin \theta}{L_{mf}^{MT}} \\ h_{me} &= \frac{L_{me}^{ua} L_{me}^{fa} \sin \theta}{L_{me}^{MT}} \\ h_{bra} &= \frac{L_{bra}^{ua} L_{bra}^{fa} \sin \theta}{L_{bra}^{MT}} \end{aligned} \quad (3.14)$$

For the biarticular flexor and extensor, the musculotendon lengths are given as

$$\begin{aligned} L_{bf}^{MT} &= \sqrt{(L_{bf}^{fa})^2 + (L_1)^2 - 2L_1 L_{bf}^{fa} \cos(\pi - \theta - \theta_1)} \\ L_{be}^{MT} &= \sqrt{(L_{be}^{fa})^2 + (L_2)^2 - 2L_2 L_{be}^{fa} \cos(\theta - \theta_2)} \end{aligned} \quad (3.15)$$

and the moment arms are,

$$\begin{aligned} h_{bf} &= \frac{L_{bf}^{fa} L_1 \sin(\pi - \theta - \theta_1)}{L_{bf}^{MT}} \\ h_{be} &= \frac{L_{be}^{fa} L_2 \sin(\theta - \theta_2)}{L_{be}^{MT}} \end{aligned} \quad (3.16)$$

where

$$\begin{aligned} L_1 &= \sqrt{(L_{bf}^{sh})^2 + (L_{ua})^2 - 2L_{ua} L_{bf}^{sh} \cos \theta_{sh}} \\ L_2 &= \sqrt{(L_{be}^{sh})^2 + (L_{ua})^2 + 2L_{ua} L_{be}^{sh} \cos \theta_{sh}} \end{aligned}$$

and

$$\begin{aligned} \theta_1 &= \arcsin \left(\frac{L_{bf}^{sh} \sin \theta_{sh}}{L_1} \right) \\ \theta_2 &= \arcsin \left(\frac{L_{be}^{sh} \sin \theta_{sh}}{L_2} \right) \end{aligned}$$

Remark1: The velocity of musculotendon can be determined by the derivation of the musculotendon length.

Remark2: Based on literature [5], the musculotendon length is defined as the length of the entire muscle-tendon unit from the origin to insertion; the muscle fascicle length is defined as the length of a small bundle of muscle fibers from the tendon of origin to the tendon of insertion; and the muscle length is the distance

from the most proximal fibers at the origin to the most distal fibers at the insertion. For simplification, in this study, the muscle length is assumed equal to the muscle fascicle length.

3.2.5 Joint dynamics

The joint torque T is calculated by:

$$T = T_f - T_e - T_L \quad (3.17)$$

where T_f and T_e are torques produced by the flexors and extensors, respectively, T_L is the load torque applied to the elbow joint. Muscle torques are determined by muscle force F^M , moment arms h , and additional torques, i.e., additional torque $= \epsilon_{AT}E(\theta(t) - \theta(t - t_d))$. The additional torque is generated by muscles during delay period.

$$T_f = F_{mf}^M h_{mf} + F_{bf}^M h_{bf} + F_{bra}^M h_{bra} + \epsilon_{AT}E_f(\theta(t) - \theta(t - t_d)) \quad (3.18)$$

$$T_e = F_{me}^M h_{me} + F_{be}^M h_{be} + \epsilon_{AT}E_e * (\theta(t) - \theta(t - t_d))$$

The dynamic properties of a joint are determined by:

$$I\ddot{\theta} + B\dot{\theta} = T \quad (3.19)$$

$$\kappa = K_f + K_e = K_{mf}^M \cdot h_{mf}^2 + K_{me}^M \cdot h_{me}^2 + K_{bf}^M \cdot h_{bf}^2 + K_{be}^M \cdot h_{be}^2 + K_{bra}^M \cdot h_{bra}^2 \quad (3.20)$$

$$B = 0.03\kappa, \quad B \geq 0 \quad (3.21)$$

where I is the moment of inertia about elbow. Based on the parallel-axis theorem, I is determined by the body mass M , forearm length $L_{forearm}$ and hand effective length L_{hand} [18],

$$\begin{aligned} I = & 0.006 \cdot M \cdot (0.297 \cdot L_{hand})^2 + 0.006 \cdot M \cdot (0.506 \cdot L_{hand} + L_{forearm})^2 + \\ & 0.016 \cdot M \cdot (0.303 \cdot L_{forearm})^2 + 0.016 \cdot M \cdot (0.43 \cdot L_{forearm})^2 \end{aligned} \quad (3.22)$$

where B is the coefficient of viscosity, which is related to joint stiffness of muscles [107, 108], θ is the elbow joint angle, κ is joint stiffness, K_f and K_e are joint stiffness of flexor and extensor muscle groups; while K_{mf}^M , K_{me}^M , K_{bf}^M , K_{be}^M and K_{bra}^M are the muscle stiffness of monoarticular flexor and extensor, biarticular flexor and extensor, and brachialis, respectively. Passive elastic joint force is ignored. The muscle stiffness is defined under isometric condition as follows [2]:

$$K^M = \frac{\partial F^{CE}}{\partial L^M} = 2d \cdot \frac{F_{max}}{L_o^M} \cdot A(t) \cdot (\tilde{L}^M - 1) \quad (3.23)$$

3.3 Model parameters estimation

Based on the model described in last section, to customize musculotendon model for specific muscles, the following parameters should be specified: the peak isometric muscle force F_{max} ; the optimal muscle fascicle length L_o^M ; musculotendon length L^{MT} , the moment of arm h ; the tendon slack length L_s^T ; the maximally elongated musculotendon length L_{max}^{MT} and muscles intrinsic maximum shortening velocity V_{max} .

In these parameters, L^{MT} and h are calculated by equations listed in section 3.2.4. L_s^T can be calculated by equation (3.10). Thus the parameters L^{MT} , h , L_s^T and L_{max}^{MT} are only determined by the attachment point (insertion and origin) and optimal muscle fascicle length of special muscles. Furthermore, a review of literature [109] suggests that the maximum muscle contraction velocity V_{max} can be expressed in optimal fiber length L_o^M per second, i.e., 10 L_o^M per second for young adults and 8 for older adults. The peak isometric muscle force (F^{MAX}) is assumed to be proportional to physiological muscle cross-sectional area (PCSA) [110]. To sum up, the positions of attachment points, the optimal muscle fascicle length and the PCSA are required to be estimated on subject-specific basis.

Figure 3.4: The procedure of parameters estimation for subject-specific musculoskeletal model by ultrasonography measurement. The muscle attachment points, muscle optimal length and muscle maximum force output are estimated to identify the parameters of the musculoskeletal system model. The details of procedure (1), (2) and (3) are presented in section 3.3.1, 3.3.2 and 3.3.3, respectively.

The procedure of parameter estimation for subject-specific case is shown in Fig. 3.4. Ultrasound images are analyzed off-line to find the muscle architecture parameters. The overall procedure includes two steps: 1) Obtain measurable parameters from ultrasound measurements *in vivo*; 2) Calculate unmeasurable parameters from the measured parameters by the known proportions. These proportions are calculated from measured properties of anatomical structure and the correlations between different portions of musculoskeletal system. The correlations are calculated from cadaver data proposed in literatures [4–7]. The details of the parameter estimation are presented in section 3.3.1, 3.3.2 and 3.3.3.

In this study, a B-mode ultrasonography scanner with 12 MHz (central fre-

quency), 38 mm line array probe (Ultrasonix Sonix RP) is used for data acquisition. Healthy subjects sit on a height adjustable chair with a solid back support. Coupling gel was applied to enhance ultrasound conduction between the probe and skin surface.

3.3.1 Estimation of insertion and origin

In anatomy, the biceps has two tendons in the shoulder and one tendon in elbow, and the triceps are three head muscles. The brachialis lies right under the biceps, which is a more powerful flexor of the elbow. The anatomical origin and insertion points are listed in Table 3.1. The procedure of measurement is described in annotations of the table. The regular guidelines about musculoskeletal ultrasonography can be found in literatures [111–113] and open-accessing tutorials (the European Society of Musculoskeletal Radiology). Two data images from our experimental measurement are also shown in Figs. 3.5 and 3.6. The white fringe of the humerus bone and the dark muscle fascicle can be easily observed in the image. The origin and insertion points of the muscles are assumed to be concentrated at centroids of muscle attachment areas. The coordinates of those muscle attachment points are then identified with respect to the corresponding skin surface under the middle point of the ultrasound probe in the local coordinate system.

Figure 3.5: Longitudinal ultrasonography shows the normal appearance of the long head of the biceps tendon. This image is collected from subject 1.

Table 3.1: Anatomy of insertions and origins

Muscles	Insertion / origin	Anatomical position	Ultrasound measurement
Biceps	Insertion	the tuberosity of radius and supinates the forearm	Yes ^a
	Origin (long head)	the scapula at the supraglenoid tubercle	Yes ^b
	Origin (short head)	the tip of coracoid process of the scapula	No
Triceps	Insertion	the proximal end of olecranon process of ulna	Yes ^c
	Origin (long head)	the infraglenoid tubercle of scapula	No
	Origin (lateral and medial head)	the posterior surface of humerus	No
brachialis	Insertion	coronoid process and the tuberosity of the ulna	Yes ^d
	Origin	the anterior surface, distal half of the humerus	Yes ^e

^a The patient sits with the arm resting in front of them on a table. The probe is held longitudinally over the antecubital fossa.

^b The patient sits with the dorsal aspect of the forearm resting on the anterior surface of their thigh. The probe is held longitudinally over the supraglenoid tubercle.

^c The patient sits and holds the arm in the ‘crab’ position. The probe is held longitudinally near the olecranon.

^d The patient sits with the arm in an extension position over the table. The probe is held transversely over the ulna.

^e The patient sits with the arm resting in front of them on a table. The probe is held longitudinally along the humerus.

However, due to the limitations of musculoskeletal ultrasound, some insertions

Figure 3.6: Longitudinal ultrasonography of the medial aspect of the distal triceps insertion shows the tendon attachment to the olecranon. This image is collected from subject 3.

and origins (marked by “No” in the column of “ultrasound measurement” in table 3.1) can not be clearly identified. For example, triceps long head, which is covered by teres minor, infraspinatus and deltoid, is difficult to be identified from the complicated pattern of the ultrasound image. To calculate the position that can not be obtained from ultrasonography, the relative position of attachment points to the limb is derived from the reported cadaver data and measured data. Take short origin head of biceps for instance. If we assume the measured ratio of L_{mf}^{ua} to L^{ua} is k_1 , the corresponding ratio obtained from literature is k_2 , and the ratio of L_{bf}^{sh} to L^{ua} obtained from literature is k_3 , then the estimated value of L_{bf}^{sh} can be calculated as,

$$L_{bf}^{sh}(estimate) = L^{ua}(measure) \cdot k_3 \cdot \frac{k_1}{k_2}$$

where $L_{bf}^{sh}(estimate)$ is the estimated value, $L^{ua}(measure)$ is the measured upper arm length from anthropometry.

3.3.2 Estimation of optimal muscle fascicle length

Since the muscle fascicle length can not be directly acquired by ultrasonography, a geometrical model of musculotendon complex is introduced (see in Fig.

Figure 3.7: The geometrical model of musculotendon complex. All muscle fibers are assumed to be arranged in parallel with the same length, and tendon is inserted with pennation angle. When the muscle fibers shorten, pennation angle increases, but the width of the muscle remains constant.

Figure 3.8: The longitudinal view of the ultrasonography of brachialis and biceps brachii. The image is collected from subject 1. The ultrasound probe is put on the anterior part of upper arm near the elbow joint. The abbreviations in the figure are explained in section 3.3.2.

3.7). This model is implemented into the ultrasound image of muscles to estimate the muscle fascicle length. One example is shown in Fig. 3.8. The pennation angle (α) is measured from the image, and then the whole muscle fibre length (L^M) is given by [91],

$$L^M = L_a + \frac{L_{b1}}{\sin \alpha_p} + \frac{L_{b2}}{\sin \alpha_p} \quad (3.24)$$

where L_a is the visible part of the muscle fibre, L_{b1} and L_{b2} are the distance of fiber distal end point to the superficial aponeurosis and the distance of fiber proximal end to the bone, respectively.

Based on the force-length property presented by Zajac [23], when muscle force equal to the maximum isometric force (F^{MAX}), it is expected that the muscle fascicle length L^M equals to the optimal muscle-fiber length (OML) L_o^M [4, 5, 105]. Therefore, the estimated muscle fascicle length under maximum voluntary isometric contraction (MVC) is regarded as the OML.

Furthermore, because different heads of muscles can not be identified from ultrasound image in our experiment, only the fascicle length of the whole muscle is obtained by ultrasonography, such as brachialis, biceps brachii and triceps. It is assumed that the measured length is the average value of the fascicle length of different heads. Thus OMLs of different heads are calculated by the ratio of the OMLs of different heads to the average OML. This ratio is derived from previous literatures [5–7]. For example, if we assume that $L_o^{mf}(literature)$ and $L_{o-bic}^M(literature)$ are the literature's OMLs of biceps long head and average OML of biceps brachii respectively, then the estimated OML of biceps long head $L_o^{mf}(estimate)$ is given by

$$L_o^{mf}(estimate) = L_{o-bic}^M(measure) \cdot \frac{L_o^{mf}(literature)}{L_{o-bic}^M(literature)}$$

where $L_{o-bic}^M(measure)$ is the measured average OML of the biceps brachii.

3.3.3 Estimation of maximum isometric force

Maximum isometric muscle force (F^{MAX}) is assumed to be proportional to physiological muscle cross-sectional area (PCSA) regardless of age and sex [23, 110]. The ultrasonic method has been used to measure the PCSA of the muscle for a long time [110]. The general method of ultrasound measurement for PCSA is to move the ultrasound scanner around the upper arm to draw the outline of the muscle, then the PCSA can be measured by enclosing the outline. In this

Figure 3.9: The transverse view of the ultrasonography of flexor muscle groups in subject 4, white line draws the approximate outline of the PCSA of flexor muscle groups, which includes Biceps brachii and Brachialis (The right board of muscle groups is out of this figure). The muscles' width and thickness are measured by this figure to evaluate the value of PCSA.

study, for simplicity, the PCSA of muscle is modeled as a rectangle, the muscle width (lateral dimension) and thickness (anteroposterior dimension) are measured to evaluate PCSA. The ratio of F^{MAX} to PCSA represents the maximum muscle stress, which has been assigned values ranging from 220 to 360 kPa [114, 115]. In current research, a value of 330 kPa is assumed for muscles in the upper limb [116].

A typical transverse view of the ultrasound image is shown in Fig. 3.9. It is daunting to identify different muscles in the muscle group by the ultrasound image. Therefore, only the values of combined PCSA for whole flexor/extensor groups are measured by ultrasonography, and then the value of PCSA of the individual muscles can be calculated from the combined PCSA by the reference table [5–7]. For example, if it is assumed the ratio of PCSA of the brachialis to the combined PCSA of flexor muscle groups (Biceps+Brachialis) is $k_{fle-PCSA}$, and the measured

PCSA of flexor muscle groups is $PCSA_{fle}(measure)$, then the calculated PCSA of brachialis ($PCSA_{bra}(estimate)$) is determined by,

$$PCSA_{bra}(estimate) = PCSA_{fle}(measure) \cdot k_{fle-PCSA}$$

the estimated maximum isometric muscle force of brachialis (F_{bra}^{MAX}) is given as,

$$F_{bra}^{MAX} = 330000 \cdot PCSA_{bra}(estimate)$$

3.4 Experimental protocol

Several healthy male subjects (n=4, age 21-28) without any known neurological disorders participate in the experiment. Each person sits on a chair with adjustable height and a solid back support, places the forearm on a horizontal plane (table). The shoulder is approximatively in 120° flexion and 80° abduction. The maximal isometric torques (MIT) is measured during maximal voluntary elbow flexion in the order at 45° and 135° of elbow angle. A non-elastic band is wrapped around the hand and coupled to a dynamometer fixed at the end of the table. The lever arm is determined as the perpendicular line between the band and the elbow joint. Subjects are required to achieve MIT in 1.5 s and maintain it for further 2 s. The highest force is used for analysis. Trials are performed in a random order with a resting period of 2 minutes between the trials.

To evaluate the performance of the model, elbow movements of flexor and extensor muscle groups are recorded and analyzed. Elbow angle time series are recorded using a multi-function data acquisition system (MP150, BIOPAC, USA). In detail, the elbow angle time histories are measured by two-axis goniometer (Biometrics, 110mm) and recorded by MP150 through the transformer (TSD130B, BIOPAC, sample rate 2000 Hz). The signals are amplified (gain=5000) and low-pass filtered by the module of DA100C in MP system (cutoff frquence=5000 Hz).

3.5 Results

3.5.1 Estimated parameters

In this study, the musculoskeletal parameters of the subjects participating the experiments are estimated. Table 3.2 showed the data of the musculoskeletal parameters of flexor and extensor muscle groups in the upper arm of four subjects, and those reported in the literatures [4–7]. The values of non-subject-specific parameters are also listed in this table. Some selected experiment photos are shown in Appendix. The data suggests that our estimated values agree with the values reported in literatures [4–7].

Table 3.2: Musculoskeletal model parameters

Subject Specific Parameters	Subjects					Subject Nonspecific Parameters	
	1	2	3	4	Literature ^a		
Age (year)	29	29	25	25		r	0.05
M (kg)	75	63	68	80	98 ¹	τ_{rise} (s)	0.012(f), 0.02(n) ⁱ
L_{hand} (m) ^b	0.14	0.13	0.13	0.13		τ_{fall} (s)	0.06
$L_{forearm}$ (m) ^c	0.25	0.24	0.25	0.24	0.28 ¹	a	1.5
F_{max-mf} (N) ^d	115.5	98.5	118.9	108.7	92.4 ¹ , 82.5 ² , 82.5 ³ , 51.8 ⁴	b	8.0
F_{max-me} (N)	316.6	271.3	321.6	291.5	267.3 ¹ , 346.5 ² , 336.6 ³ , 242.2 ⁴ h	c	0.0866
F_{max-bf} (N)	108.9	92.9	112.1	102.5	85.8 ¹ , 69.3 ² , 69.3 ³ , 57.8 ⁴	d	-3.188
F_{max-be} (N)	158.0	135.4	160.5	145.5	155.1 ¹ , 141.9 ² , 221.1 ³ , 118.8 ⁴	c^{PE1}	23
$F_{max-bra}$ (N)	250.8	211.2	257.4	231	184.8 ¹ , 178.2 ² , 217.8 ³ , 254.4 ⁴	k^{PE1}	0.046
L_{mf}^{fa} (m)	0.06	0.055	0.065	0.06	0.0675 ¹	L^{PE1}	1.17
L_{me}^{fa} (m)	0.04	0.04	0.04	0.04	0.045 ¹	η	0.01
L_{mf}^{ua} (m)	0.285	0.255	0.28	0.26	0.329 ¹	c^{PE2}	-0.02
L_{me}^{ua} (m)	0.22	0.2	0.22	0.2	0.26 ¹	k^{PE2}	-21.0375
L_{bra}^{fa} (m)	0.025	0.02	0.025	0.02	0.025 ¹	L^{PE2}	0.70222
L_{bra}^{ua} (m)	0.155	0.14	0.15	0.145	0.182 ¹	k_{mf}^T (N/m)	42919
L_{bf}^{fa} (m)	0.06	0.055	0.065	0.06	0.0675 ¹	k_{me}^T (N/m)	46307
L_{be}^{fa} (m)	0.04	0.04	0.04	0.04	0.045 ¹	k_{bf}^T (N/m)	41784
L_{bf}^{sh} (m)	0.03	0.025	0.03	0.025	0.036 ¹	k_{be}^T (N/m)	37888
L_{be}^{sh} (m)	0.027	0.025	0.028	0.025	0.03 ¹	k_{bra}^T (N/m)	71467
L_{mf}^{ua} (m) ^e	0.31	0.28	0.30	0.28	0.36 ¹	c_{s-mf}^T	1.1
L_{o-mf}^M (m) ^f	0.146	0.134	0.150	0.138	0.128 ² , 0.136 ³ , 0.1561 ⁴	c_{s-me}^T	1.3
L_{o-me}^M (m) ^g	0.112	0.104	0.114	0.106	0.093 ² , 0.084 ³ , 0.1028 ⁴	c_{s-bf}^T	1.1
L_{o-bf}^M (m)	0.174	0.159	0.177	0.163	0.145 ² , 0.15 ³ , 0.1809 ⁴	c_{s-be}^T	1.4
L_{o-be}^M (m)	0.142	0.131	0.143	0.133	0.127 ² , 0.102 ³ , 0.1762 ⁴	c_{s-bra}^T	1.1
L_{o-bra}^M (m)	0.095	0.086	0.092	0.086	0.099 ² , 0.093 ³ , 0.0942 ⁴	ϵ_{AT} (N*m*deg ⁻²)	0.01

^a The data obtained from 1: [4]; 2: [5]; 3: [6]; 4:[7].

^b Defined as the distance between wrist joint and knuckle II of middle finger.

^c Defined as the distance between ulnar styloid and elbow joint.

^d $F_{max} = \text{PCSA}(\text{m}^2) * 330(\text{kpa})$.

^e Defined as the distance between glenohumeral joint and elbow joint.

^f Defined as the optimal muscle fascicle length (the length of a small bundle of muscle fibers from the tendon of origin to the tendon of insertion)[5]

^g value of L_{o-me}^M is chosen as the optimal fascicle length of the lateral head.

^h PCSA of monoarticular extensor was calculated using the combined values of the medial and lateral heads.

ⁱ To take into account the phenomenon that the muscle activation starts from doublets or triplets of spikes following with very short intervals in fast movement [117], the small value of rise time τ_{rise} (12 ms) is chosen for the simulation of fast movement in this study. Contrarily, 20 ms is chosen for normal movement.

3.5.2 Prediction of maximum voluntary isometric torque

To check the validity of parameters, The estimated values are employed into the model presented in section 3.2 to predict the MIT of elbow flexion. The performance of estimation is evaluated by comparison of the experimental recorded value with model prediction. Modeling and simulations are conducted by Matlab 7.1 (R14) and Simulink.

The comparison between the model prediction and experiment results is shown in table 3.3. The results show that the simulation output approximately agrees with the experiment record. Since most of the model predictions are smaller than experiment record, The errors may be caused by the imperfections of parameters' calculation. For example, the moment arms of muscles may be underestimated by the algorithm. However, the performance of parameters estimation is still acceptable for model development.

Table 3.3: Maximum voluntary isometric torque

Elbow joint		MIT of Subjects (N*m)			
		1	2	3	4
45°	Experiment	25.3	21.9	30.2	16.8
	Simulation	22.1	17.5	23.3	19.8
90°	Experiment	32.2	27.3	39.6	23.7
	Simulation	29.0	22.60	30.9	25.9

3.6 Discussion & Conclusion

In this chapter, we have built a subject-specific musculoskeletal model of the human upper limb via ultrasonography for the first time. The ultrasound imaging technology, the geometrical model of the upper limb and the cadaver data collected from the literatures are used to estimate the parameters of the musculotendon structure *in vivo*. The estimation is validated by simulation and experimental results. This study provides a feasible approach which allows researchers to develop a subject-specific model.

In this study, the moment arms and the musculotendon length are defined as a trigonometric function depending on the elbow and shoulder angles. These definitions have been used in the 2-D musculoskeletal modeling in the previous study [2]. Alternatively, other studies give a polynomial form to determine the relationship between the parameters of the muscles and the joint angles. However, the coefficients of the polynomial can not be identified *in vivo* by ultrasound measurement. Therefore, the trigonometric function is used as its coefficients can be readily measured.

Chapter 4

Verification of Threshold Control Theory on Single Joint Movements

4.1 Introduction

In chapter 3, a delicate subject-specific musculoskeletal model has been developed. In this chapter, the validation of threshold control theory and its extensions is given with this musculoskeletal model. The threshold control theory is one of the major theories to explain the mechanism of human motor control system. As mentioned in section 2.4.2, many claims had been proposed to support the feasibility of threshold control theory.

However, these claims as well as attempts to refute them [44, 45, 118] were based on simulation results with the musculoskeletal system model in which the

viscoelastic properties of musculoskeletal system are inadequately represented or not at all. For instance, most models that studied threshold control theory ignore the tendon compliance of muscle, so that the controller controls the joint angle by adjusting the appropriate musculotendon lengths (i.e., the whole length of the musculotendon complex) based on the muscle spindles feedback [45, 50]. In reality, however, the muscle spindle feedback is not directly related to the musculotendon length but to the muscle fiber length. Therefore, the tendon compliance, which determines the relationship between the muscle fiber length and musculotendon length, must be considered in modeling. Additionally, when the tendon compliance is ignored, the contraction velocity becomes proportional to the angular velocity, which is not physiologically sound [23].

Recently, many researchers have noted this problem and investigated the feasibility of the threshold controller to the completed musculoskeletal model [11, 46, 119]. A study of the latest threshold control model presented by Pilon et al. [46, 120] suggested that the threshold controller can generate a stable fast movement, even with a wide range of proprioceptive delay. In their model, the tendon compliance and muscle passive stiffness are indirectly represented by the experimental static invariant characteristic (IC), which represents the relationship between the muscle torque and joint angle when the joint angular velocity goes to zero. However, the model presented in Pilon’s paper might be regarded as a “macroscopic” model, as the lower level structure of the human motor system, such as muscles, is not detailedly described. Kistemaker et al. [11] tried to test the applicability of the λ -controller for fast movements by a musculoskeletal model with more details. However, the joint viscosity and passive force-length characteristic of muscles are still not fully represented in their investigation.

Besides the incomplete representation of the musculotendon properties, another problem for previous modeling is that the physiological parameters (e.g.

muscle fiber length, musculotendon length and maximum muscle contraction force) of the models proposed in the previous literatures are not accurately estimated on subject-specific basis. Since the modeling and simulation results are significantly affected by the accuracy of estimated values of musculotendon complex parameters [88], the model built on the data from the cadaver is not capable to provide quantitative insights in analyzing the human movement and evaluating the performance of the controller.

To overcome the shortcoming of previous studies and provide convincing insights for threshold control theory, a physiology-based threshold control model is established to predict human elbow movement. In this model, the viscoelastic properties of the musculotendon are adequately described to reflect the physiological reality. The parameters of the musculoskeletal structure are measured *in vivo* by experiments. The details of model and parameters estimation have been presented in chapter 3.

The controller is designed based on the latest version of the threshold control theory [46]. Two extensions to improve performance are tested. Firstly, the control signals are sent intermittently to improve the speed of the movement. Secondly, the feedback on the actual joint angular velocity is replaced by the difference between the actual and desired velocity to reduce the responding time of the system and improve the peak velocity of the movement. The details about the control scheme is presented in section 4.2.

Afterwards, some experimental results in measuring the elbow angle and EMG during elbow horizon movements with different speeds are presented. The experiment method is presented in section 4.3. The experimental results are then compared with the simulation results of the threshold control model to evaluate the controller's ability to reproduce the experimentally observed movements in section 4.4. A fixed step-size (step-size:0.01s) ordinary differential equation solver

based on the Bogacki-Shampine formula is used to numerically solve the neuromusculoskeletal model. The model is set up and simulations are carried out in Matlab 7.1 (R14) and Simulink. A preliminary stability analysis is given in section 4.6. Finally, discussion and conclusion are given in sections 4.5 and 4.7. For relevant abbreviations of this chapter, please see chapter “List of Abbreviations and Symbols”.

4.2 Control scheme

In this study, the threshold control theory [46, 121] is applied to simulate the control scheme of motor neuron circuits. It is assumed that the muscle activation depends on the difference between the actual and threshold arm position. To drive the flexor and extensor groups co-active, the static thresholds of flexor and extensor muscle groups are defined by two cooperative commands: reciprocal command R and co-activation command C (Fig. 4.1). i.e., the static thresholds of flexor λ_f and extensor λ_e are given by:

$$\lambda_f = R + C, \quad \lambda_e = R - C \quad (4.1)$$

In detail, the reciprocal command R sets a threshold angle of elbow, i.e., all elbow muscles are silent when the elbow angle equals to the reciprocal command, but any deviation from these angles will evoke activation of appropriate muscles to resist the deviation [122]. The co-activation command C shifts the pattern of the threshold configuration of the elbow into different muscle thresholds for opposing muscle groups. So the flexor and extensor muscle groups become “co-active”. In this study, R and C commands are approximatively ramp-shaped. For quality identification, the R command is similar to the desired trajectory. The C

Figure 4.1: Threshold control of muscle activation. The excitation is produced in proportion to the difference between actual joint angle and threshold joint angle (λ). The thresholds of flexor and extensor muscle groups (λ_f and λ_e) are cooperatively controlled by two central commands (R and C). Without the C command, a common threshold position (λ_f1 and λ_e1) are specified for both muscle groups (dash-dotted lines), thus only one muscle group can be stimulated at one time. In the presence of C command, it will shift the thresholds of these groups in opposite directions (λ_f2 and λ_e2), thus the muscles will be co-active in the zone ($2C$) surrounding R .

command starts from zero at the beginning of the movement and finally decreases to zero whereas the R command is maintained after the end of movement, because the co-activation of opposing muscle groups decreases after the end of movement [123]. The shape of command C are defined by best matching the estimated and experimental trajectories. The desired trajectory is designed as minimal jerk trajectories [49, 124] rather than the experimental data, as it might be implausible to regard the endpoint oscillations of the actual movement as a part of the desired movement.

Based on the latest threshold control scheme [46], the threshold angle of the muscle depends on the velocity and variables characterizing intermuscular interactions. The velocity feedback of the model is due to the muscle length feedback from spindles and its gain μ depends on the dynamic sensitivity of spindle afferents [44, 46]. i.e., the dynamic threshold angles λ_f^* and λ_e^* , and corresponding muscle excitation E_f and E_e are given by,

$$\begin{aligned}\lambda_f^* &= \lambda_f - \mu\omega(t - t_d) - rE_e \\ \lambda_e^* &= \lambda_e - \mu\omega(t - t_d) + rE_f\end{aligned}\tag{4.2}$$

$$\begin{aligned}E_f &= [\lambda_f^* - \theta(t - t_d)]_0^1 \\ E_e &= [\theta(t - t_d) - \lambda_e^*]_0^1\end{aligned}\tag{4.3}$$

where $\omega(t - t_d)$ is the joint angular velocity at time $t - t_d$. t_d is the feedback time delay. The feedback gain μ is optimized to minimize the total sum of the differences between simulated and experimental movements. The optimal values are identified using a grid search method. The muscle excitation E is normalized to interval $[0, 1]$ by the maximum value ($[x]_0^1 = 0$ if $x < 0$). The portions of rE_e and rE_f are the component characterizing reflex inter-muscular interaction, which includes the

Figure 4.2: System block of the musculoskeletal model with the threshold controller.

reciprocal inhibition of motor neurons mediated by Ia interneurons. r represents the strength of reciprocal inhibition with $0 < r < 1$. Then the muscle excitations are sent to muscle groups to generate muscle forces and joint movements. The block diagram is shown in Fig. 4.2.

Based on literatures [11, 12], two extensions have been proposed to improve the performance, whose applicability is then tested in this study.

Firstly, several neurophysiological and behavioral studies suggest that the central nervous system (CNS) might control human movements intermittently rather than continuously during voluntary movements of the finger, wrist and elbow [125–128]. It is suggested that this intermittency effect can be helpful to improve the movement speed to better correspond with experimentally observed data [11, 12]. Intermittent control is implemented by updating R and C at a frequency of 10 Hz in Fig. 4.2. Feedback is updated continuously.

Secondly, McIntyre and Bizzi suggested that feedback on the actual velocity alone should be replaced by the feedback on the difference between the actual and desired velocities. This modification would increase the peak velocity of movement

Figure 4.3: System block of the threshold control model with feedback on the difference between the actual and desired velocities.

and reduce the responding time of the system [12]. i.e., the dynamical threshold is redetermined as,

$$\begin{aligned}\lambda_f^* &= \lambda_f + \mu(\omega_{Ref} - \omega(t - t_d)) - rE_e \\ \lambda_e^* &= \lambda_e + \mu(\omega_{Ref} - \omega(t - t_d)) + rE_f\end{aligned}\tag{4.4}$$

where ω_{Ref} is the desired elbow angular velocity. The block diagram of the extended controller is shown in Fig. 4.3.

In following discussions, to distinguish the original and extended threshold controller, the continuous threshold controller, intermittent threshold controller and continuous threshold controller with the feedback on the difference between the actual and desired velocities are marked as continuous controller, intermittent controller and diff. controller, respectively.

4.3 Experimental method

To evaluate the performance of the model, elbow movements and EMG activation of flexor and extensor muscle groups are recorded and analyzed.

4.3.1 Experimental protocol

Several healthy male subjects ($n=4$, age 21-28) without any known neurological disorders participate in experiments. Each person sits on a chair with adjustable height and a solid back support, places the forearm on a horizontal plane. The shoulder is approximatively in 120° flexion and 80° abduction. In response to a sound signal, they move their forearm from an initial position of about 9° to the remembered targets (about 80° for normal movement and 90° for fast movement) with eyes closing. In all trials, the participants are instructed to move under two different speeds: 1) 10 trials as “comfortable speed” (peak velocity $140^\circ - 170^\circ$ per second). This motion is called as “normal movement”. 2) 10 trials as “maximum speed” (peak velocity $300^\circ - 600^\circ$ per second). This motion is called as “fast movement”. Before the trials, participants practice until they can move fast with minimal overshoot. Breaks of 5 min are interspersed between normal and fast movement. At the end of experiments, participants lift a dumbbell as slowly as they can to record the value of the EMG signal during the maximum voluntary contraction.

4.3.2 Data collection and analysis

Surface EMG and elbow angle time histories are recorded using a multi-function data acquisition system (MP150, BIOPAC, USA). In detail, the elbow

angle time histories are measured by two-axis goniometer (Biometrics, 110mm) and recorded by MP150 through the transformer (TSD130B, BIOPAC, sample rate 2000 Hz). The signals are amplified and low-pass filtered by the module of DA100C in MP system.

On the other hand, myoelectric activity is recorded (EMG100C, sample rate 2000 Hz) from biceps brachii and triceps brachii. Two electrode channels are placed over the muscles and a reference electrode is placed at Processus styloideus radii. Each channel includes a set of two electrodes (EL503, BIOPAC) at the center position in the most flexed/extended status. Before attaching the electrodes, subject's skin is prepared by lightly abrading with skin exfoliate to remove dead skin, and cleaned with alcohol swab to remove oil and dust on the surface. These preparations are helpful to reduce the skin impedance to less than 60 k Ω [129]. To improve the signal quality, the sEMG signals are amplified and band-pass filtered.

A raw sEMG signal is a voltage with positive and negative values, which must be processed into a form that can be used to estimate muscle activation. To accomplish this, the linear-phase high-pass FIR digital filter (No. of coefficients: 800, cutoff frequency: 5-30 Hz) is used to remove DC offsets and low frequency noise of the raw signals [130]. We take absolute values of each point to rectify the signal, and normalize the rectified signal by the peak rectified EMG value obtained during a maximum voluntary contraction. Finally, a low-pass filter (FIR, No. of coefficients: 800, cutoff frequency: 10 Hz) is applied to the resultant signal to remove the high-frequency components, so the envelope of the sEMG signal is derived as the muscle activation [131], a typical procedure is shown in Fig. 4.4.

Figure 4.4: The estimation of muscle activation from sEMG (Fig. 4.4.a). First a high-pass filter is used to remove DC offsets and low frequency noise; then the absolute values are taken to rectify the signal (Fig. 4.4.b); Finally, a low-pass filter is employed to move the high-frequency components of the normalized rectified sEMG to get the muscle activation (Fig. 4.4.c).

4.4 Experiment and simulation results

The quality of simulations is estimated by the correlation (R_c^2) between the experimental and simulated traces with a level of significance $P < 0.01$. The outcome of the control system is considered to reproduce the experimental movement if $R_c^2 > 0.95$. Then the performance of the control system is quantified by calculating the root-mean-squared (RMS) values between the simulated and experimentally observed trajectory. It is necessary to eliminate the time shift before calculating the value of RMS. Firstly, the lag yielding the highest cross-correlation is identified by calculating the cross-correlation function between experimental and simulated data. The lag is slightly modified to best match the experimental and simulated traces. Secondly, the RMS value between the simulated and experimental data is calculated, after the time shift is eliminated based on the indicated lag.

4.4.1 Verification of the threshold control model and two extensions

Firstly, we test whether the threshold control system can reproduce the experimental trajectory and whether the two extensions can improve the performance. The performances of these controllers are estimated through a comparison of the recorded elbow movements with the simulated movements by different controllers (continuous controller, intermittent controller and diff. controller). The input R and C commands are the same for the three controllers, and the feedback delay $t_d = 30$ ms.

Figs. 4.5 to 4.12 show the experimental record and simulation results in two trials (normal and fast movements) of one participant (subject 3), which is discussed here as a representative of the other results. The parameter values of the musculoskeletal model are estimated from subject 3 *in vivo* (shown in Table 3.2).

From these figures, the following properties can be observed:

1) The three controllers can all realize the desired task and approximately reproduce the experimental movement. However, the velocity profiles show that the movements generated by the continuous and intermittent version of threshold controller are slower than the experimentally recorded movements. Secondly, the intermittent controller does not significantly improve the performance as mentioned by Kistemaker [11]. Finally, the diff. controller acts more actively than the other two controllers and can efficiently improve the movement speed. This is because the diff. controller can drive the movement to follow the desired trajectory more closely than the controller with feedback on the actual velocity.

2) Based on the figures of muscle activations, it is found that the patterns generated with the continuous controller are qualitatively similar to the experi-

Figure 4.5: Experimental data and simulated joint angles acquired with continuous, intermittent and diff. controllers for the normal movement of subject 3. Continuous lines represent simulation results and recorded experimental results. Dotted lines represent the control commands. The values of RMS are listed in the figures.

Figure 4.6: Experimental and simulated joint angular velocities for normal movement of subject 3. Peak velocities are listed in the figures.

Figure 4.7: Experimental and simulated flexor muscle activations for the normal movement of subject 3.

Figure 4.8: Experimental and simulated extensor muscle activations for the normal movement of subject 3.

Figure 4.9: Experimental data and simulated joint angles acquired with continuous, intermittent and diff. controllers for the fast movement of subject 3. Continuous lines represent simulation results and recorded experimental results. Dotted lines represent the control commands. The values of RMS are listed in the figures.

Figure 4.10: Experimental and simulated joint angular velocities for the fast movement of subject 3. Peak velocities are listed in the figures.

Figure 4.11: Experimental and simulated flexor muscle activations for the fast movement of subject 3.

Figure 4.12: Experimental and simulated extensor muscle activations for the fast movement of subject 3.

mentally observed patterns. The contours of the patterns are also not severely changed by using the intermittent and diff. controllers except some spines. It suggests that some noises are introduced by the intermittent and diff. controllers. In contrast, the amplitude of spines introduced by intermittent controller is larger than that introduced by diff. controller. This implies that the side-effect of the intermittent controller is relatively larger than that of the diff. controller. i.e., the muscle activation patterns produced by the intermittent controller are rougher.

For concluding above observations, the statistical results of the average RMS values between the experimental and simulated data are shown in Table 4.1. The average ratio between the simulated peak angular velocity ($\omega_{max-sim}$) and experiment recorded values ($\omega_{max-exp}$) is listed in Table 4.2. The low RMS values indicate a good resemblance between simulated and experimentally observed trajectories. It is noted that there are no significant differences between the three controllers, so at least these two extensions are not helpful to produce a better matching movements with the experimental traces. Further results of the peak angular velocity show the movements generated by the diff. controller are faster thus better matching with desired trajectories. On the contrary, the intermittent controller has similar performance as that produced by the continuous controller. It is noted that the peak angular velocity produced with diff. controller is even higher than experimental records for the normal movement. This is because the speeds generated by the diff. controller strongly depend on the difference between the actual and desired traces. Therefore, for producing normal movement, the diff. controller will try to compensate the initial error by evoking the faster movement.

In conclusion, the diff. controller mildly improves the dynamic performance of threshold controller. This improvement is more significant for the fast movement.

Table 4.1: Average RMS values between experimental and simulated data

Controller	Movement	Subjects ^a			
		1	2	3	4
Continuous controller	Normal	1.4192°	1.4303°	1.3978°	1.4028°
	Fast	0.9302°	0.9362°	0.9571°	0.9431°
Intermittent controller	Normal	1.4036°	1.4400°	1.4025°	1.3866°
	Fast	0.9503°	0.9227°	0.9303°	0.9659°
Diff. controller	Normal	1.5024°	1.4670°	1.5314°	1.4907°
	Fast	0.9236°	0.9542°	0.9322°	0.9421°

^a Feedback delay $t_d=30$ ms, external load $T_L=0$, feedback gains are optimized to minimize values of RMS.

Table 4.2: Average ratio of the peak angular velocity between experimental and simulated data ($\omega_{max-sim}/\omega_{max-exp}$)

Controller	Movement	Subjects ^a			
		1	2	3	4
Continuous controller	Normal	0.8732	0.8607	0.8825	0.8429
	Fast	0.8007	0.7986	0.8120	0.7895
Intermittent controller	Normal	0.9362	0.8925	0.9324	0.9012
	Fast	0.8068	0.8124	0.8224	0.8036
Diff. controller	Normal	1.1201	1.1352	1.2054	1.0121
	Fast	0.9183	0.9254	0.9023	0.9152

^a Feedback delay $t_d=30$ ms, external load $T_L=0$, feed gains are optimized to minimize values of RMS.

4.4.2 Robustness to feedback delay and perturbations

To test the range of feedback delays that the system can accommodate without compromising its stability, the performance of the diff. controlled model with

external perturbations is studied in the presence of different delays. (see in Figs. 4.13 and 4.14). A strong perturbation is applied before the onset and after the offset of movement. Since the destabilizing effect of the endurable feedback time delay in fast movement is more severe than the problem in normal movement, only the situation of fast movement is discussed here. Three conclusions are derived from the simulation results: 1) the threshold control model can produce the stable kinematic output with the feedback delay up to 50 ms. The movement output of model with large feedback delays (70 ms) will be trapped in long-lasting oscillations. 2) strong perturbations do not destabilize the system at the beginning and final position, but will cause large overshoots. The overshoots are increased with the large feedback delays. 3) the time-lag of the diff. controller is remarkably smaller than the continuous controller, though the angle and velocity profile of the movement outputs with the continuous and diff. controllers do not show significant differences. It suggests the diff. controller can efficiently reduce the responding delay of the system.

4.4.3 Influence of subject-specific musculoskeletal parameter

In this section, we test whether it works by using subject-specific musculoskeletal parameters for modeling. Simulations with different musculoskeletal parameters for fast movements are conducted to test their performances. Diff. controller is applied for simulation and the simulation results are presented in Fig. 4.15. In this figure, solid lines represent the simulation outputs of the subject-specific model with musculoskeletal parameters collected from subject 1 and dash-dotted lines represent the results of cadaver-based model with parameters reported in

4.13.a: $t_d = 0$ ms, angle

4.13.b: $t_d = 30$ ms, angle

4.13.c: $t_d = 50$ ms, angle

4.13.d: $t_d = 70$ ms, angle

Figure 4.13: Simulated elbow joint angle with external perturbations for fast movement. In the figure, dash-dotted lines, solid lines and dashed lines represent the results of diff. controller, continuous controller and intermittent controller respectively. The pulse perturbations is added at the initial (arrows, time=0.3s, 5 N*m during 10 ms) and final position (arrows, time=3s, 50 N*m during 10 ms) in the presence of feedback delays t_d 0, 30, 50 and 70 ms. Desired velocity profile and control commands (dotted lines) are also shown in the figures for quantifying performance.

4.14.a: $t_d = 0$ ms, velocity

4.14.b: $t_d = 30$ ms, velocity

4.14.c: $t_d = 50$ ms, velocity

4.14.d: $t_d = 70$ ms, velocity

Figure 4.14: Simulated elbow joint angle and angular velocity with external perturbations for fast movement (continued to Fig. 4.13).

[4, 5]. The comparison of the results suggest that the model with subject-specific musculoskeletal parameters has better performance: 1) The RMS values of the subject-specific model are lower than those of cadaver-based model; 2) Subject-specific model is capable of reproducing fast movement to match experimental data, while cadaver-based model can not.

4.4.4 Conclusion of experimental and simulation study

It can be concluded from these results that the proposed threshold controllers can realize the desired task in the presence of feedback delays up to 50 ms. Additionally, the threshold controllers are also robust to external perturbations and changing of musculoskeletal parameters. Two extended versions of the threshold controller have different performances in our studies. In detail, the intermittent controller does not significantly reduce the deviation between the simulated and experimental data and also can not increase the movement speed. Additionally, it introduces noises to the movement outputs. On the other hand, though the diff. controller also introduces some noises to the movement outputs, it can efficiently improve the movement speed and reduce the responding delay of the system. Moreover, the simulation results on different musculoskeletal models suggest that the subject-specific musculoskeletal model can improve the simulation accuracy.

4.5 Discussion

4.5.1 Validity of threshold control theory

First of all, our study supports the latest literature [120] reported that the central nervous system can realize motor action by resetting the threshold position

Figure 4.15: The simulated elbow joint angle and angular velocity with the subject-specific model and the cadaver-based model for fast movement. Solid lines represent the output of the subject-specific model with parameters estimated from subject 1. Dash-dotted lines represent the output of the cadaver-based model with cadaver parameters adapted from literatures [4, 5] (see in Table 3.2), the value of moment of inertia of the cadaver-based model is $0.09363 \text{ kg}\cdot\text{m}^2$. Furthermore, the measured experimental data (dashed lines), input signals and desired angular velocity (dotted lines) are also represented. The feedback gains and input commands are specially optimized for different models.

of appropriate body segments (threshold control) and minimizing the deviation between the actual and threshold position (minimal interaction). Our study also suggests that our motor control system might be a sophisticated predictive system, i.e., the system behavior can be “pre-determined” by the predictive properties of natural, physical laws [119]. Therefore, the threshold controller with proprioceptive signals can build a spatial frame of movement reference for solving the redundancy problem, as strategy 2 shown in section 2.4.1 [121]. In detail, the threshold controller firstly limits the set of possible actions by using the presupposed commands. Then the controller reduces the restricted set into a unique one based on the interaction between neuromuscular elements and the environment.

From the viewpoint of control theory, the property of threshold controller means that the threshold control can realize the desired task just with the feedback information of the joint angle and angular velocity. Specifically, the feedback of the joint angular velocity is needed to prevent the oscillatory behavior in the endpoint due to the time-lag-related instability of natural musculoskeletal system. Our study supports the former statement by other researchers that stability is ensured with the threshold controller for the entire range of possible proprioceptive delays (20-50 ms) [46, 132, 133].

4.5.2 Difference from the latest threshold control model

As mentioned in the section 4.1, comparing with the latest version of threshold control model (Pilon and Feldman’s model [46]), more physiological details are considered in our model.

Based on our knowledge, Pilon and Feldman’s model (P & F’s model) is more like a “macroscopic” system model, which treats the whole musculoskeletal system as a “grey box”. The properties of this model are determined by parameter

identification procedures on experimental data. In our view, the flowchart of the P & F's model can be concluded as,

$$\begin{aligned} R, C &\rightarrow \lambda \rightarrow A \rightarrow \text{static muscle torque} \\ &\rightarrow T^M(\text{dynamic muscle torque}) \rightarrow \theta(\text{elbow angle}) \end{aligned}$$

In this model, the increase in the muscle torque directly depends on the number of active motor units, which is determined by the difference between the actual and the threshold angles. The relationship between the angle and muscle torque is given by the invariant characteristic (IC). This relationship is reliable, because it is derived from the experimental observation. However, this model can not predict some information generated during the intermediate process of the movement, for example, the muscle excitation and muscle force.

To remedy this shortcoming, we develop a model with “step-by-step” structure by assuming that the movement is realized step by step and the procedure of each step is modeled. The approach has two advantages: 1) it allows the calculation of different intermediate variables (e.g., muscle force or activation functions); 2) it provides better understandings about the roles of the different physiological processes. The flowchart of our model is:

$$\begin{aligned} R, C &\rightarrow \lambda \rightarrow E \rightarrow A(\text{muscle activation}) \rightarrow F^M(\text{muscle force}) \\ &\rightarrow T^M(\text{muscle torque}) \rightarrow \theta(\text{elbow angle}) \end{aligned}$$

The equations used in our model have been proven by the previous studies. The simulation results also suggest that our model has the similar performance as the latest threshold control model.

In fact, our model and P & F's model still share similar properties, since both describe the same physiological system. Firstly, the static ICs correspond to

the force-length characteristics of the musculotendon complex used in our model. Secondly, the calcium-concentration processes in the muscle activation and force-velocity properties of the musculotendon complex in our model correspond to the transformation from static ICs to dynamic ICs in P & F's model.

In summary, though structure of these two models are different, they still share similar properties. Simulation results suggest that they are both physiologically reliable model. In comparison with the latest threshold control model, our model can provide more detailed movement information.

4.5.3 Performance of extensions

To improve the performance of the threshold controller, two extensions: intermittent controller and diff. controller are tested. The dynamical output of the intermittent controller (see in Fig. 4.5 to Fig. 4.12, Table 4.1 and Table 4.2) suggests that the movement speed is not noticeably increased when the controllers send out their control signals in an intermittent fashion. Furthermore, some noises are introduced to velocity profile. This refutes the previous conclusions of Kistemaker et al. [11], which implied that the human motor control system sent out intermittent control signal instead of continuous commands, in order to shorten the responding time.

In contrast, the angle and velocity profiles of the output of the diff. controller shows higher peak velocity and shorter responding delay than the continuous controller. From an engineering point of view, the performance of threshold controller is improved by introducing this modification, though physiological validity of the modification is still subjected to verification.

It is noted that the movement trajectory of the diff. controller is strongly depending on the desired task. This fact suggests that if the desired trajectory is

perfectly constant with a real movement, there is no doubt that the diff. controller is a better choice. The problem is whether the brain can precisely predict the outcome of movement and then send a threshold motor command similar to the actual trajectory. Some studies suggest that only simple threshold trajectories are needed for human limb movement, such as ramp-shaped trajectories [44, 46, 54] and N-shape trajectories [50]. If voluntary movement is really controlled without a precisely reference trajectory, it seems that the threshold controller with the actual velocity feedback is more capable than the diff. controller. However if we apply the threshold control theory to artificial motor control, such as FES, the advantage of the diff. controller is obvious.

4.5.4 Sensitivity of feedback gain

The stability of the system is guaranteed by the proprioceptive feedback, elastic and damping musculotendon properties. Thus the feedback gains will influence the dynamic behavior of the system. Here the performances of diff. controller and continuous controller are investigated and the results are shown in Fig. 4.16. There are two observations: 1) the increasing of μ effectively reduces the overshoot of the movement, which is resulted from the initial conditions, internal properties and external load [134–136]. This effect occurs for both the continuous controller and the diff. controller. 2) the increasing of μ reduces the responding delay of the diff. controller. However, the same effect is not observed in the continuous controller. This suggests that increasing feedback gains will drive the diff. controller to follow the desired trajectory faster.

4.16.a: Angle profile with continuous controller

4.16.b: Velocity profile with continuous controller

4.16.c: Angle profile with diff. controller

4.16.d: Velocity profile with diff. controller

Figure 4.16: The dynamic responses of the system for different values of μ . Des. ω : desired joint angular velocity.

4.5.5 Further improvement of threshold control theory

Although it is proved that the threshold control is feasible in the context of single joint movements, the question still remains whether the present statement is generalizable to the human motor control under various conditions involving, for instance, multi-joint movements and gravity. Comparing to single joint systems, “interaction torques” (i.e., the movement at one joints will cause the rising of torques at another joints) and different actions of mono- and biarticular muscles [137] should be taken into account for multi-joint systems. Furthermore, in this study, the arm movement is not affected by gravity, because the arm is restricted to move in a horizontal plane without external load. If the external load and gravity is added, static errors between the desired equilibrium position and the actual final position may occur. These errors will depend on the the static properties of external torque adding to the elbow joint and the stiffness induced by muscles and feedback. The deviation from the desired position will be increased with the large external loads, if the influence of external loads is not accounted in the threshold controller. In our preliminary study, changing control commands and feedback gains can compensate the influence of normal external forces such as gravity. However, the deviation from the desired trajectory will become unacceptably large with enormous external loads, even the values of C command are adjusted to the utmost. The measures of above two issues has been discussed and applied into the threshold FES controller presented in chapters 5 and 6.

4.6 Qualitative analysis of system stability

Based on our previous study and literature review [11, 44, 54], the advantage of the threshold control theory had been proven by simulation and experimen-

tal study. However, though the previous experimental results had validated it, a mathematical proof will be more persuasive. To our knowledge, there are no explicit and systematic rules based on the muscle's mechanical properties for variables of the threshold control theory. In this section, we propose a qualitative proof that the threshold control theory is sufficient to stabilize the co-activated abundant muscle-skeletal systems. And an explicit construction of the unmeasurable neurophysiological commands of CNS will be provided as well .

As far as we know, stability is critical for successful human movements. In a stable system, the movement outcome can be predicted and the movement can be planned. e.g., the human arm can return to its prescribed path or original condition after a disturbance [138]. Static arm positions are easily stabilized by the intrinsic properties of muscles. However, the stability requirements will be more demanding for fast arm movements. Comparatively strong position- and velocity-dependent feedback and effective muscle torque controllers are necessary to realize desired task and to prevent long-lasting terminal oscillations.

In this study, the stability is defined as Lyapunov stability. Thus Lyapunov theory [139] and its extension, contraction theory [140] are chosen to analyze the stability. Lyapunov theory is the well established, widely-accepted concept in the investigation of stability of dynamic system. The contraction theory is an extension of Lyapunov theory, and can avoid finding some implicit motion integral as in Lyapunov methods, the details of contraction theory are shown in Appendix. Therefore, the final behavior of the system would be independent to the initial conditions.

To facilitate stability analysis, the threshold controlled musculoskeletal system

is described in the state-space form [139]:

$$\begin{cases} \dot{\theta} = \omega \\ \dot{\omega} = f(\theta, \omega, t - t_d) \end{cases} \quad (4.5)$$

where $f \in \mathbb{R}^1$ is given by $f(\theta, \omega, t - t_d) = \frac{T_f - T_e - T_L - B\dot{\theta}}{I}$, θ and ω are the state variables representing the angle and angular velocity, respectively. Note that $f(\theta, \omega, t - t_d)$ is a nonlinear piecewise function. Obviously, the original threshold control model (continuous controller) and extended threshold control model (diff. controller) have the same stability.

Based on the experimental studies [141], T can be represented as an empirical exponential function,

$$T_f = a(e^{\alpha E_f} - 1), \quad T_e = a(e^{\alpha E_e} - 1) \quad (4.6)$$

where a and α are constants, and specializes the transformation efficiency of muscle activations into torques. The unit of the variable a is “N*m”; It is acceptable that we assume transformation efficiencies of flexor and extensor are the same if antagonist is symmetric.

In following contents of this section, we will qualitative analyze the system stability from simplified condition to complete condition. In detail, the simplest condition is discussed firstly, then followed by the system with external load, joint viscosity and time delay.

4.6.1 Stability analysis of simplified model

To provide a preliminary understanding about the system stability, following preconditions are applied to simplify the analysis:

- (i) $t_d = 0$;
- (ii) $T_L = 0$;
- (iii) $B = 0$.

Then, the equation (4.5) can be rewritten as:

$$\begin{aligned} f &= \frac{T_f - T_e - T_L - B\dot{\theta}}{I} \\ &\approx \frac{a(e^{\alpha E_f} - 1) - a(e^{\alpha E_e} - 1)}{I} \end{aligned} \quad (4.7)$$

The model described by above equation is defined as the simplified threshold control model. Therefore, for the simplified threshold control model, the Jacobian matrix is given by

$$J = \begin{bmatrix} 0 & 1 \\ a_{21} & a_{22} \end{bmatrix} \quad (4.8)$$

where J represents the Jacobian matrix of the threshold control model. Additionally, we introduce the variable $\theta^* = \theta + \mu\omega$ for simplicity.

Based on equations (4.1), (4.3), (4.2), (4.4) and (4.7), the possible operation regions of the simplified threshold control model can be summarized in the following 3 cases.

Case 1:

$$\theta^* > R + \frac{1-r}{1+r}C$$

Introduce above condition to equations 4.1, 4.2, 4.3 and 4.7, we have,

$$\begin{aligned} E_f &= 0 \\ E_e &= \theta - \lambda_e^* = \theta - \lambda_e + \mu\omega \end{aligned} \quad (4.9)$$

then $f(\theta, \omega, t)$ becomes

$$\ddot{\theta} = \frac{-a(e^{\alpha E_e} - 1)}{I} = \frac{-a(e^{\alpha(\theta - \lambda_e + \mu\omega)} - 1)}{I} \quad (4.10)$$

and the corresponding elements of the Jacobian matrix are

$$\begin{bmatrix} a_{21} = -\frac{a\alpha}{I}[e^{\alpha(\theta - \lambda_e + \mu\omega)}] \\ a_{22} = -\frac{a\alpha\mu}{I}[e^{\alpha(\theta - \lambda_e + \mu\omega)}] \end{bmatrix} \quad (4.11)$$

Therefore, the equilibrium point (θ_{EP}) under this region should be determined by

$$\theta_{EP} = \lambda_e = R - C$$

Case 2:

$$\theta^* < R - \frac{1-r}{1+r}C$$

Introduce above condition to equations 4.1, 4.2, 4.3 and 4.7, we have,

$$E_f = \lambda_f^* - \theta = \lambda_f - \mu\omega - \theta \quad (4.12)$$

$$E_e = 0$$

then $f(\theta, \omega, t)$ becomes

$$\ddot{\theta} = \frac{a(e^{\alpha E_f} - 1)}{I} = \frac{a(e^{\alpha(\lambda_f - \mu\omega - \theta)} - 1)}{I} \quad (4.13)$$

and the corresponding elements of the Jacobian matrix are

$$\begin{bmatrix} a_{21} = -\frac{a\alpha}{I}[e^{\alpha(\lambda_f - \mu\omega - \theta)}] \\ a_{22} = -\frac{a\alpha\mu}{I}[e^{\alpha(\lambda_f - \mu\omega - \theta)}] \end{bmatrix} \quad (4.14)$$

Therefore, the equilibrium point under this region should be calculated by

$$\theta_{EP} = \lambda_f = R + C$$

Case 3:

$$R - \frac{1-r}{1+r}C < \theta^* < R + \frac{1-r}{1+r}C$$

Introduce above condition to equations 4.1, 4.2, 4.3 and 4.7, we have,

$$\begin{aligned} E_f &= \lambda_f^* - \theta \\ &= \frac{R}{1-r} + \frac{C}{1+r} - \frac{\theta^*}{1-r} \\ E_e &= \theta - \lambda_e^* \\ &= \frac{\theta^*}{1-r} - \frac{R}{1-r} + \frac{C}{1+r} \end{aligned} \tag{4.15}$$

then $f(\theta, \omega, t)$ becomes

$$\ddot{\theta} = \frac{a(e^{\alpha E_f} - 1) - a(e^{\alpha E_e} - 1)}{I} = \frac{a(e^{\alpha(\frac{R}{1-r} + \frac{C}{1+r} - \frac{\theta^*}{1-r})} - 1) - a(e^{\alpha(\frac{\theta^*}{1-r} - \frac{R}{1-r} + \frac{C}{1+r})} - 1)}{I} \tag{4.16}$$

and the corresponding elements of the Jacobian matrix are

$$\begin{bmatrix} a_{21} = \frac{-a\alpha}{I(1-r)}[e^{\alpha E_f} + e^{\alpha E_e}] \\ a_{22} = \frac{-a\alpha\mu}{I(1-r)}[e^{\alpha E_f} + e^{\alpha E_e}] \end{bmatrix} \tag{4.17}$$

Therefore, the equilibrium point under this region should be calculated by

$$\theta_{EP} = R$$

To sum up, the operation regions of the system can be divided into 3 parts as shown in Fig. 4.17. Then we can get the following statements based on the mathematical analysis.

Figure 4.17: Three operation regions defined in Cases 1 - 3. Note that all EPs are located on the θ axis and all EPs are located outside the regions except EP3, for example, EP1 is located in the region of Case 3.

Statement 1: *Consider the threshold control model given in equations (4.1) - (4.3). If*

- (i) *the system works in the operation regions determined by Cases 1 - 3;*
- (ii) $r < 1; \mu > 0; I > 0;$
- (iii) *the product, $a \times \alpha > 0$.*

then the threshold control model is strictly stable in the operation regions.

Proof: The proof is done through verification of the Jacobian matrices obtained in Cases 1 - 3 above. Note that the eigenvalues of the Jacobian matrices are not fixed. But as the elements a_{21} and a_{22} of the Jacobian matrices (equation (4.8)) in this case are negative at any time, the real parts of both eigenvalues are negative. With the Jacobian matrix uniformly negative in all operational regions determined by Cases 1 - 3, the system starting in the regions will converge exponentially to the equilibrium points, i.e. it is strictly stable. This has completed the proof.

Statement 2: *Consider the threshold control model given in equations (4.1) - (4.3) with the conditions,*

- (i) $r < 1; C > 0; \mu > 0; I > 0$, and
- (ii) *the product, $a \times \alpha > 0$.*

under which Cases 1 - 3 apply, then there is only one equilibrium point which is given by

$$\begin{cases} \theta_{EP} = R \\ \omega_{EP} = 0 \end{cases} \quad \text{where the subscript EP represents equilibrium point.}$$

Proof: It is verified through analysis of the equilibrium points as follows:

If $r < 1$ applies, and the operational regions are determined by cases 1 - 3 of the threshold control model. Hereby, the equilibrium point (EP) of the system is determined from equation (4.5) as $\dot{\theta} = 0$, and $\dot{\omega} = 0$. Note that the first equation $\dot{\theta} = \omega = 0$ implies $\theta^* = \theta$ as $\theta^* = \theta + \mu\omega$. Then, the EPs for Cases 1 - 3 are given by:

for Case 1 (from equation (4.10))

$$\theta_{EP1} = R - C \quad (4.18)$$

for Case 2 (from equation (4.13))

$$\theta_{EP2} = R + C \quad (4.19)$$

for Case 3 (from equation (4.16))

$$\theta_{EP3} = R \quad (4.20)$$

The EPs for Cases 1 and 2 are out of their own operation regions, which implies that the system in the operation regions will finally converge to the unique EP, $\theta_{EP3} = R, \omega_{EP1} = 0$ in the region of Case 3. The operation regions in the θ - ω plane are illustrated in Fig. 4.17. This result is also verified by the previous experimental and simulation data.

Remark 1 : According to the previous study by St-Onge [44], the command R specifies the equilibrium state of the system. We extend these statements by providing mathematical proofs for them. Statement 1 established the stability of the threshold control model. The stability of the system can be guaranteed

under the condition stated in the statement and the joint angle converges to the EPs. Statement 2 reveals that a unique equilibrium point can be obtained with appropriate selection of the parameters. Thus, our stability analysis prove the simplified threshold control model can provide physiologically sound activation patterns of an arm reaching task.

Remark 2 : Three cases represent various stages of the continuous movement. For example, in the experiment presented in section 4.3, the elbow movement can be divided into 3 stages: 1) initial acceleration stage (small joint angle and joint angular velocity); 2) middle deceleration stage (large joint angle and joint angular velocity); 3) final stable stage (middle joint angle and small joint angular velocity). Thus, cases 1, 2 and 3 are corresponding to stage 2, 3 and 1, respectively.

4.6.2 Simplified model with external load

Secondly, we extend the stability properties derived in section 4.6.1 with more complicated model:

- (i) $t_d = 0$;
- (ii) $T_L \neq 0$;
- (iii) $B = 0$.

If the external torque is considered in the threshold control model, equation (4.7) should be rewritten as:

$$I \frac{d^2\theta}{dt^2} = T_e - T_f - T_L$$

In this case, the state-space format of the system (equation (4.5)) becomes

$$\begin{cases} \dot{\theta} = \omega \\ \dot{\omega} = f(\theta, \omega, t), \text{ with } f(\theta, \omega, t) = \frac{T_e - T_f - T_L}{I} \end{cases}$$

The elements of Jacobian matrix (equation (4.8)) can be determined as:

$$\begin{aligned} a_{21}^* &= \frac{dT_e}{Id\theta} - \frac{dT_f}{Id\theta} - \frac{dT_L}{Id\theta} = a_{21} - \frac{dT_L}{Id\theta} \\ a_{22}^* &= \frac{dT_e}{Id\omega} - \frac{dT_f}{Id\omega} - \frac{dT_L}{Id\omega} = a_{22} - \frac{dT_L}{Id\omega} \end{aligned} \quad (4.21)$$

where a_{21} and a_{22} are the elements of the Jacobian matrix of the simplified model. Obviously, the stability of system can not be guaranteed as shown in statement 1. However, if the external torque is constant to joint angle and angular velocity, stability of the system is not affected. Note that all three equilibrium points will be shifted due to the external torque.

4.6.3 Simplified model with joint viscosity

As a further investigation of the system stability driven by threshold controller, here the system with more complicated conditions is discussed:

- (i) $t_d = 0$;
- (ii) $T_L \neq 0$;
- (iii) $B \neq 0$.

Equation (4.7) should be extended to:

$$I \frac{d^2\theta}{dt^2} + B \frac{d\theta}{dt} = T_e - T_f - T_L \quad (4.22)$$

The elements of Jacobian matrix (equation (4.8)) can be determined as:

$$\begin{aligned} a_{21}^* &= \frac{dT_e}{Id\theta} - \frac{dT_f}{Id\theta} - \frac{dT_L}{Id\theta} = a_{21} - \frac{dT_L}{Id\theta} - B \\ a_{22}^* &= \frac{dT_e}{Id\omega} - \frac{dT_f}{Id\omega} - \frac{dT_L}{Id\omega} = a_{22} - \frac{dT_L}{Id\omega} \end{aligned} \quad (4.23)$$

Since the variable of B is the non negative constant, it is observed that the factor of joint viscosity can improve the stability of the system, i.e., the disturbance caused by unexpected load and long time delay will be partially compensated by the joint viscosity.

4.6.4 Simplified model with time delay

Finally, we discuss the system stability with complete condition, i.e.,

- (i) $t_d \neq 0$;
- (ii) $T_L \neq 0$;
- (iii) $B \neq 0$.

If $t_d \neq 0$, the simplified λ model is a nonlinear time-delay system. Due to the complexities of analysis, we transfer the simplified model to a linear time-delay function by Taylor series.

$$\begin{aligned} I \frac{d^2\theta}{dt^2} &= a\alpha E_f - a\alpha E_e \\ \Rightarrow f_{delay}(\theta, \omega, t - t_d) &= \frac{a\alpha E_f - a\alpha E_e}{I} \end{aligned} \quad (4.24)$$

Note that f_{delay} is a linear time-delay function. The characteristic function associated with system presented in equation (4.24) is:

$$P(s, t_d) = s^2 + (b'_1 + b'_2 s)e^{-t_d s} \quad (4.25)$$

where $b'_1 = \frac{\partial f}{\partial \theta}$, $b'_2 = \frac{\partial f}{\partial \omega} = \mu b'_1$

After algebraic manipulations on equation (4.25), we obtain the time-delay limit, d^* as

$$d^* = \mu \frac{\beta}{\tan \beta} \quad (4.26)$$

where

$$\beta = \arccos\left[\frac{-\mu^2 \dot{b}_1 + \sqrt{\mu^4 \dot{b}_1^2 + 4}}{2}\right]$$

for $\mu^4 \dot{b}_1^2 + 4 > 0$ and $\beta \neq 0 \Rightarrow (\dot{b}_1 \neq 0 \ \& \ \mu \neq 0)$. So, to insure the stability of the whole system, the following two inequations must be assured:

$$d^* > d_{real},$$

$$\mu^4 \dot{b}_1^2 + 4 > 0$$

where d_{real} is the anatomical value of the time-delay.

4.6.5 Conclusion of qualitative stability analysis

Our calculations qualitative prove that the threshold controller is able to generate a stable movement, if its parameters do not exceed limitations. These limitations are determined by muscle properties, muscle geometry, geometric properties of the linkage system, external load and time delay. Following preliminary conclusions are derived from the stability analysis:

1. If the system can be stable, it will have a unique EP;
2. The final joint angle is predetermined by the reciprocal commands R , and shifted by variable of T_L ;
3. Joint viscosity can enhance the system stability.

4.7 Conclusion

Our study in this chapter proves that the threshold controller is sufficient to generate single joint movements in presence of physiologically possible proprioceptive feedback delays. Since the latest version of the threshold controller [46]

seems incapable of generating movements fast enough to match experiment data during fast movement. Two extensions were proposed by previous researchers to improve the performance, i.e., the intermittent threshold controller and diff. controller. In this study, we examined the validity of the threshold control models using an detailed musculoskeletal model of the elbow on the specific subject developed by ultrasound measurement *in vivo*. The parameter values of the controller are optimized to make the model reproduce the kinematic responses to match experimental data as close as possible. It is shown that the threshold model is robust in reproducing experimental movement patterns and generating stable output despite substantial feedback delays and strong perturbation. Furthermore, the diff. controller improves the movement peak velocity and reduces the responding delay, although some noises are also introduced. In contrast, the intermittent version does not show significantly advantage on the improvement of performance.

In sum, this study has demonstrated that the physiology-based threshold control is a feasible solution to explain the mechanism of control for single joint movements. Comparing the original threshold controller and its two extensions, the diff. controller depicted in equations 4.1 and 4.4 has the best performance in the engineering sense.

Chapter 5

Development and Verification of Threshold FES Controller on Upper Limb Movement

5.1 Introduction

In this chapter, we intend to develop new FES control strategy with the knowledge of the human central nervous system. After comparing various hypotheses for human motor control mechanism, the threshold control theory is deemed as the most credible candidate for engineering application. From the viewpoint of control engineer, the mechanism of the threshold control theory suggests that limb movements can be adequately controlled without solving the “inverse dynamics problem”. Previous literature [11] and our previous study all show that the performance of the threshold controller is not noticeably affected by the changing of

inertial parameters of the musculoskeletal model, even without re-optimizing the parameters of controller. It seems that the threshold control theory can be used to develop an efficient and easy-to-use FES controller.

Currently, few researchers had tried to implement threshold control theory into FES technique, and only preliminary study on single-joint movement is conducted [142]. Based on our knowledge, it is the first time that the threshold control theory is employed in FES technique for multiple joints movement. The control commands of original threshold control model of the natural human motor system depend on two factors: 1) the difference between the actual and desired threshold joint angle. 2) the feedback of joint angular velocity, which is due to the feedback of the muscle spindle [44, 46]. Our study (shown in following contents of this chapter) suggests that the original threshold controller is incapable of generating stable movements with large feedback delays, because the time-lag-related instability of FES-driven musculoskeletal system is relatively severer than that of natural system. Thus a feedback of joint angular acceleration is introduced to determine the commands, which is assumed to represent the feedback of the golgi tendon organs of all joint muscles. The simulation study for single joint movement verifies the feasibility of this modification to prevent the destabilizing effects caused by the large feedback delays.

In this chapter, we study the applicability of threshold FES controller for two different physiologically motivated human upper limb musculoskeletal models, i.e., the model with 5 muscles, single joint and the model with 7 muscles, two joints. The following contents are organized as follows:

Model with 5 muscles, single joint:

Firstly, the threshold controller is replanted to control the behavior of elbow joint with FES. It is noted that the muscle excitation-activation couples under

external electric stimulation is different with the natural procedure described in section 3.2.1. The activation dynamics under FES is modeled in section 5.2.1.

Secondly, the control scheme based on threshold control theory is presented in section 5.2.1. Three control strategies are proposed based on the original version and extensions of threshold control theory.

Afterwards, simulation study is conducted to evaluate the controller's ability to realize the desired task and prevent destabilizing effects of different perturbation, external load and feedback delays. The simulation results are shown in section 5.2.2.

Finally, discussions and conclusions are given in sections 5.2.3 and 5.2.4.

Model with 7 muscles, two joints:

In the last part of discussion on a model of single joint, the validity of threshold FES controller has been proven. However, the real human musculoskeletal is a multi-joint system. To test the performance of threshold FES controller in more physiologically reliable system, we develop a model including 7 lumped muscles and the joint movement of elbow and shoulder. The model of anatomical arrangement, coordinates of elbow and hand, and external load are created. The values of new model parameters for added elements are derived based on literatures. The control scheme for two joints model is mostly similar with that for single joint model, the difference lies in the strategy to coordinate the action of muscle for generating two joints movement. This strategy is introduced in section 5.3.1. Afterwards, simulation study is conducted to test the system performance to realize desired hand trajectory with different perturbations, external load and feedback delays (see in section 5.3.2). The discussions and conclusions are given in section 5.4 and 5.5.

For relevant abbreviations of this chapter, see Glossary .

5.2 Study of single joint model

There are two purposes for developing and investigating a single joint model. Firstly, the threshold FES controller is validated by using a simple musculoskeletal model including major physiological properties. Secondly, the two novel extensions are tested in this simple model.

5.2.1 System description

Model of FES for paralyzed arm

Here we present the proposed controller and the model including the major properties of muscle and segmental dynamics occurring during FES. The musculoskeletal model of arm is presented as three segments connected by two hinge joints (glenohumeral joint and the elbow joint, Fig. 5.1). In this study, the arm is restricted to movement in horizontal plane and actuated by five lumped muscles: first monoarticular elbow flexor (Biceps long head), second monoarticular elbow flexor (Brachialis), a monoarticular elbow extensor (Triceps Lateral head and Medial head), a biarticular elbow flexor (Biceps short head), and a biarticular elbow extensor (Triceps long head), (see in Fig. 5.1). The path of a muscle is represented by a straight line joining the centroid of the muscle attachment sites.

The continuous-time signal with the modulated pulse width and constant pulse frequency (50 Hz) is used to drive each muscle group, which is provided by an electrical stimulator (see Fig. 5.2). Muscle activation is regarded as the co-effect of spatial and temporal summation by a nonlinear recruitment curve [143], a nonlinear activation-frequency relationship, and a nonlinear first-order calcium dynamics [87]. Since the fatigue significantly increases with increasing stimulation

frequency, magnitude and duration, a fatigue/recovery model [144] is incorporated. An additional constant time delay is also added to present finite conduction velocities in the membrane system and delays from the chemical reactions [145]. The muscle active force is driven by the muscle activation, which is interacted with the muscle passive force to produce the resultant force of the muscle group.

For each muscle, we model the dependence of muscle force on the muscle fascicle length, muscle contraction velocity and muscle activation, as shown in Fig. 5.2. In detail, the muscle is modeled as a modified Hill-type unit consisting of a contractile element (CE), a parallel elastic element (PE), and a series elastic element (SEE). The SEE is combined with tendon compliance into one element [23]. The tendon is represented as an elastic element. It is assumed that the tendon force varies linearly with a change in length as tendon is stretched from its slack length. The details about the contraction dynamics, tendon compliance, anatomical arrangement and joint dynamics are shown in section 3.2.

Recruitment:

The isometric recruitment curve (IRC) is normalized between 0 and 1 and is described by:

$$u(t) = \begin{cases} 0, & W(t) \leq w_{thr}, \\ \frac{1}{w_{sat} - w_{thr}}(W(t) - w_{thr}), & w_{thr} < W(t) < w_{sat}, \\ 1, & W(t) \geq w_{sat}. \end{cases} \quad \begin{matrix} (5.1) \\ (5.1') \\ (5.1'') \end{matrix}$$

where $W(t)$ is the pulse width, u_t is the normalized portion of motor units recruited, w_{thr} is a threshold pulse width (recruit deadband), and w_{sat} is a saturation pulse width.

Frequency effect:

Figure 5.1: The geometric relations of the elbow for FES single-joint movement. To simplify, a hinge joint with no wrap-around insertions of muscles is used to describe the joint geometry. 5 antagonist muscles are included. The condition of external loading is simulated by the spring and damping elements attached at the endpoint. θ is the elbow joint angle, and counterclockwise rotation is defined as positive. Therefore, full extension corresponds to 0 rad, and full flexion corresponds to π rad. The range of motion of elbow is from 0° (Extension) to 140° (Flexion) (Adapted from Luttgens and Hamilton [97]). The should joint angle θ_{sh} is fixed to 120° .

Figure 5.2: Muscle actuator under FES stimulation. This figure shows the block diagram of the stimulated muscle model. The stimulation pulse width are restricted by the limitation and modulated by the output of the controller. Note the constant time-delay shown in the figure represent the delay caused by the conduction and chemical reaction in membrane system, whose value is chosen as 25 ms.

It is known that the force generated by the muscle is varied with frequency of stimulation pulse. This effect is termed as the force-frequency characteristic and can be defined by [146]

$$\nu = \frac{(k_f f)^2}{1 + (k_f f)^2} \quad (5.2)$$

where ν represents the normalized amount of activation affected by the frequency f , k_f is the shape factor.

Calcium dynamics:

Since muscles can not be activated or relaxed instantaneously, the delay between muscle excitation and the muscle activation [98] can be described by a first-order differential equation based on the Hill-type model [2].

$$\dot{a}(t) = \frac{(u \cdot \nu)^2 - u \cdot \nu \cdot a}{\tau_{rise}} + \frac{u \cdot \nu - a}{\tau_{fall}} \quad (5.3)$$

where $a(t)$ is the activation of a non-fatiguing muscle, the rise time τ_{rise} and relaxation time τ_{fall} are time constants for the calcium dynamic of muscles [87].

Muscle fatigue:

In the FES system, if muscles are electrically stimulated for a long time, the muscle fatigue can cause a drop in the peak muscle torque, which is especially severe to paralyzed patients. Former research shows that the full stimulation will cause approximately 50% reduction over 100 seconds [147], and it may also cause a shift in the recruitment deadband. From the aspect of patients, there are mainly two reasons that cause fatigue: 1) One is due to the physiological factor, i.e., the ability of muscle to produce force is decreased over time. 2) The other is due to the mental factor. i.e., the brain is becoming bored or tired with the action. For the paralyzed patient which is treated with the FES system, only the muscle fatigue

due to the physiological factor is considered here. Moreover, it is also found that the fatigue rate strongly depends on the stimulation frequency [148, 149]. We use the function $p(t)$ to describe this property,

$$\dot{p}(t) = \frac{(p_{min} - p)a\psi}{\tau_{fat}} + \frac{(1 - p)(1 - a\psi)}{\tau_{rec}} \quad (5.4)$$

where the frequency factor ψ are calculated as,

$$\psi = 1 - \beta + \beta(f/100)^2 \quad \text{for } f < 100 \text{ hz} \quad (5.5)$$

where β is the shape factor. τ_{fat} is the time constant of fatigue, τ_{rec} is the time constant of recovery, and p_{min} is the minimum fitness. As the fatigue is related with the stimulation frequency, the frequency factor ψ is introduced. Note that the fatigue factor $p(t)$ in (5.4) is a variable without dimension, and it is set as a ratio to the normal muscle activation.

Therefore, after compensating the frequency effect and muscle fatigue, the final activation of the fatiguing muscle is modeled as

$$A(t) = a(t) \cdot p(t) \quad (5.6)$$

Control scheme

In this study, we try to design a controller which can mimic the function of CNS in voluntary movement to realize the desire task. The pulse width of stimulation is modulated by the desired controller to adjust the muscle contraction. Three control strategies are studied and compared to develop the optimized controller.

1) λ FES controller

λ FES controller is the FES controller directly employed from the typical threshold controller. In λ FES controller, two control commands are given to

coactivate the flexor and extensor groups: 1) reciprocal command R which specifies a common threshold of stimulation pulse width for both muscle groups, 2) co-activation command C which shifts the thresholds of these groups in opposite directions. The relationship between these commands refers to Fig. 4.1. Considering the physiological means, R is the desired trajectory and C starts from zero at the beginning of the movement, and finally decreases to zero at the end of movement. The static threshold stimulations (represented as joint angle) of flexor λ_f and extensor λ_e are given by:

$$\lambda_f = R + C, \quad \lambda_e = R - C \quad (5.7)$$

Due to the physiological process of “sensory-motor integration”, i.e., the motor neurons integrate the descending commands and proprioceptive feedback to generate muscle activation [3, 18]. In dynamics, it is assumed that the threshold angle and pulse width of stimulation depend on the velocity and variables characterizing intermuscular interactions. The velocity feedback of the model due to the muscle length feedback from spindles and its gain μ depend on the dynamic sensitivity of spindle afferents [44, 46]. This is the typical structure of threshold controller, which had been verified for single joint voluntary movement in the presence of physiologically possible feedback delays [44, 46].

2) Ref. FES controller

Compared with motor control for healthy people, the FES control for paralyzed patient is more challenging [150]. Firstly, the time-lag related destabilizing effects of FES system is more severe than that of natural one, as the transformation from electric stimulation to mechanical movement will introduce additional delay. Secondly, some beneficial factors in stabilizing the kinematics in the natural system are missing in FES control system, such as “twitch contraction” [117] and the intrinsic elasticity of muscles during the delay period [46].

Therefore, to improve the performance of the λ FES controller, the feedback on actual velocity alone is replaced by the feedback on the difference between actual and desired velocity. This extension of λ FES controller is marked as Ref. FES controller.

3) Acc. FES controller

Acc. FES controller is the extension of Ref. FES controller by introducing the joint angular acceleration feedback. It is supposed that the angular acceleration feedback might represent the response of sensors related to the change in acceleration. The maximum endurable feedback delay is expected improved by including this modification.

Since the Acc. FES controller is extended from Ref. FES controller and λ FES controller, only the formulas and block diagram (Fig. 5.3) of Acc. FES controller are shown in rest part of this section. The dynamic stimulation threshold (in terms of joint angle) λ_f^* and λ_e^* depend on the static counterpoints λ_f and λ_e , joint angle θ , angular velocity ω and angular acceleration ξ are given by:

$$\begin{aligned} Z_f &= [\lambda_f^* - \theta(t - t_d)]_0^1 \\ Z_e &= [\theta(t - t_d) - \lambda_e^*]_0^1 \end{aligned} \quad (5.8)$$

$$\lambda_f^* = \lambda_f + \mu(\dot{R} - \omega(t - t_d)) + k_\xi(\ddot{R} - \xi(t - t_d)) - rZ_e \quad (5.9)$$

$$\lambda_e^* = \lambda_e + \mu(\dot{R} - \omega(t - t_d)) + k_\xi(\ddot{R} - \xi(t - t_d)) + rZ_f$$

$$W = Z * (w_{sat} - w_{thr}) + w_{thr} \quad (5.10)$$

where W is the pulse width of stimulation, $\omega(t - t_d)$ and $\xi(t - t_d)$ are the joint angular velocity and acceleration at time $t - t_d$, respectively. t_d is the feedback time delay. $\mu > 0$ and $k_\xi > 0$ are the gains of velocity and acceleration feedback,

Figure 5.3: Block diagram of threshold FES control (Acc. FES controller). Note that 1) the feedback delay t_d presented the sensory feedback delay, which is different to the delay shown in figure 5.2. 2) the skeletal dynamics describes the equations of motion of the skeleton.

respectively. They represent the dependency of the threshold on velocity and acceleration can influence the damping of the system. The process variable Z is normalized to interval $[0 \ 1]$ by the maximum value ($[x]_0^1 = 0$ if $x < 0$). r represents the strength of reciprocal inhibition with $0 < r < 1$. The portion rZ_e and rZ_f are the component simulating the reflex inter-muscular interaction, which represents the reciprocal inhibition of motor neurons mediated by Ia interneurons.

5.2.2 Simulation results

The quality of simulations is estimated by the correlation coefficient (R_c^2) between desired and simulated traces with a level of significance $P < 0.01$. The outcome of control system is regarded to realize desired task if $R_c^2 > 0.95$. Then the performance of the control system is quantified by calculating the root-mean-squared (RMS) values between simulated and desired trajectory. It is necessary to eliminate the time shift before calculating the value of RMS. Firstly, the cross-

correlation function is calculated based on the desired and simulated data. And this function determines the time lag corresponding to the highest cross-correlation. Secondly, the lag is slightly modified to best match the desired and simulated trajectories. Finally, the RMS value between desired trajectory and the simulated data, time shifted with the indicated lag, was calculated.

First of all, we test the system performance with λ FES controller, Ref. FES controller and Acc. FES controller in the presence of different feedback delays. The simulation results is shown in Figs. 5.4 and 5.5. The musculoskeletal parameter values refer to Table 5.1. The subject-specific parameters are measured from a young healthy male by ultrasound measurement, and the nonspecific parameters are collected from literatures. The input R and C commands used in the three controllers are same. The following results can be concluded from the simulation results: 1) The low RMS values with the directly replanted threshold controller indicate the ability that the threshold controller realize the desired task with small feedback delays. 2) The introducing of the feedback on the error between the simulated and desired trajectory can significantly improve the peak velocity of the movement output and reduce the response delay of the system. 3) In the presence of large feedback delays (>10 ms), the trajectories produced by the simulation with λ FES controller are significantly different from the desired trajectory and the outcome is trapped in long-lasting oscillation at the final position. Contrarily, the simulation results suggest that the Acc. FES controller is capable of producing desired movements in this condition. Furthermore, it is a problem that all controllers can not produce the velocity fast and smooth enough to match the desire task, though the Acc. FES controller has a better performance than others.

To test the range of feedback delays that the system with Acc. FES controller can accommodate without compromising its stability, the performance of the model

Figure 5.4: Simulation results of three threshold controllers with different feedback delays. row 1-3 show the time histories of kinematic data (column 1: elbow angle; column 2: angular velocity) and of three threshold controllers with feedback time delay t_d equal to 0, 10, 40 ms, respectively. The dotted lines represent the desire elbow angle/angular velocity and input C command. The dash-dotted lines, dashed lines and solid lines represent the simulation obtained with λ FES controller, Ref. FES controller and Acc. FES controller, respectively. The RMS values between the simulated and desired trajectory are listed as following: 1) When $t_d = 0$ ms, RMS with λ FES controller: 4.1495° ; RMS with Ref. FES controller: 3.1906° ; RMS with Acc. FES controller: 2.8486° . 2) When $t_d = 10$ ms, RMS with λ FES controller: 3.7774° ; RMS with Ref. FES controller: 3.1774° ; RMS with Acc. FES controller: 2.4843° . 3) When $t_d = 10$ ms, λ and Ref. controllers can not produce a stable movement; RMS with Acc. FES controller: 2.5251° .

Figure 5.5: Continued to figure 5.4. row 1-3 show the pulse widths of stimulations (column 1: stimulation for flexor muscle groups; column 2: stimulation for extensor muscle groups) of three threshold controllers with feedback time delay t_d equal to 0, 10, 40 ms, respectively. The dash-dotted lines, dashed lines and solid lines represent the simulation obtained with λ FES controller, Ref. FES controller and Acc. FES controller, respectively.

Figure 5.6: Simulated elbow joint angle and angular velocity with external perturbations for FES single-joint movement. These results are obtained with Acc. controlled models. The pulse perturbations is added at the final position (arrows, time=2.5s, 30 N*m during 10 ms) in the presence of feedback delays t_d 0,20,40 ms. Desired angle and velocity profiles (dotted lines) are also shown in the figures for quantifying performance.

with external perturbations are studied in the presence of different delays. The simulation results are shown in Fig. 5.6. A strong perturbations are applied after the offset of movement. It suggests that the Acc. FES controller can produce stable responses even with the feedback delays up to 40ms. Strong perturbations will cause a short-period overshoot but do not destabilize the system at the final position.

5.2.3 Discussion on operation range and feedback delay

First of all, our studies suggest that the threshold control theory can be “borrowed” to FES control system. It suggests that the λ controller can realize the desired task with merely the feedback information of joint angle and angular velocity. But due to the relatively severe time-lag-related instability of FES-driven musculoskeletal system, the feedback of joint angular velocity is needed to prevent the oscillatory behavior in the endpoint. Furthermore, considering the function of GTOs, it is attempted to improve the model performance by including the feedback of the joint angular acceleration. However, two problems need to be solved before introducing this feedback. Firstly, the GTOs start firing in response to active tension of muscle fibers [151]. In other words, they might only influence “future” muscle activation but do not change the current value. It is assumed that this effect might be compensated when considering the feedback delay, i.e., the feedback of GTOs might be deemed to directly change dynamic threshold if feedback delay is larger than the restoring period of GTOs. Secondly, the activation of GTOs depends on the active muscle tension, that means the feedback of GTOs of individual muscle might not directly relate to the whole joint angular acceleration. Thus we assumed that the joint angular acceleration reflects the “global” influence of GTOs of all elbow muscles. In the other words, when acceleration equals to zero, one antagonist muscle groups might be active to compensate the passive force of another muscle groups, the active force output is still equal to zero. Thus the “global” feedback of GTOs should also be equal to zero.

To quantify the entire possible range of feedback delays for stable outcome with Acc. FES controller, the relationship of the operation range of feedback gains and the proprioceptive delays are investigated by simulation. The operation range of Acc. FES controller is shown in Fig. 5.7. The values of musculoskeletal

parameters refer to Table 5.1. The applicable schemes of feedback gains and delays are identified by grid-search method in simulation results. In detail, we check the stability of the simulated traces with different feedback gains and delays. The stability is quantified by the definition of Lyapunov stability, i.e., 1) the overshoot in the final state should be reduced, 2) the deviation between the simulated traces and desired trajectory must be negligible after limited time. With Acc. FES controller, total about 270,000 traces are tested to identify about 4,700 stable states. (t_d : 1-71 ms, μ : 0.12-0.42 s, k_ξ : 0-0.015 s², computation equipments: 3 computers with P4 2.8GHz CPU and 1 GB of RAM.) It suggests that the Acc. FES controller can endure the feedback delay up to 47 ms. Furthermore, the operation range of feedback delays derived from simulation can provide a qualitative reference for feedback gains selection.

In this section, only single joint movement is discussed. Note that the statement of this section is not generalizable to the multi-joints movement. The instability caused by feedback delay in this movement will be more severe than that existed in single joint movement. For example, the operation range of feedback gains will be reduced in the threshold controller for the multi-joint system. This problem is caused by the factors of “interaction torques” and different actions of mono- and biarticular muscles [137]. Over here, the “interaction torques” represents the phenomenon that the movement at one joint might increase the torque at another joint.

5.2.4 Brief summary

Due to the complexity of human musculoskeletal system, it is a difficult task for FES controller to coordinate the redundant muscles well and generate the appropriate stimulus to individual muscle. In this study, we employed a credible

5.7.a: μ Vs. k_ξ Vs. t_d in fast movement

5.7.b: μ Vs. t_d in fast movement

5.7.c: k_ξ Vs. t_d in fast movement

5.7.d: μ Vs. k_ξ in fast movement

Figure 5.7: The operation range of feedback gains μ and k_ξ to stable the FES single joint system with feedback delay (t_d). The fatigue rate $p(t)$ equals to 1. Points in the figure (5.7.a) present possible values of parameters to stable the system with different feedback delays. The cutaway view of figure (5.7.a) are given in Fig. (5.7.b), (5.7.c) and (5.7.d) to clarify the relationship between t_d , μ and k_ξ . Especially, the operation range of feedback gains under different feedback gains are shown in Fig. (5.7.d).

control theory - threshold control theory - to the FES control system. To improve the performance and extend the application of the system, two extensions are added to the original threshold control theory. The simulation results show that this FES control system provides satisfactory tracking performance and is stable and robust under various circumstances.

5.3 Study on two joints model

5.3.1 System description

Model of paralyzed arm

In this section, the proposed controller and the model describing major properties of muscle and segmental dynamics occurring during FES are given. The musculoskeletal model of the arm is presented as three segments connected by two hinges joints (glenohumeral joint and the elbow joint, Fig. 5.8). In this study, the arm was restricted to movement in horizontal plane and are actuated by seven lumped muscles, which are: 1.Brachialis (Elbow Flexor); 2.Biceps long head (Elbow Flexor); 3. Triceps Lateral head and Medial head (Elbow Extensor); 4. Biceps short head (Biarticular Flexor); 5. Triceps long head (Biarticular Extensor); 6. Pectoralis major (Shoulder Flexor); 7. Posterior Deltoid (Shoulder Extensor). The path of a muscle is represented by a straight line joining the centroid of the muscle attachment sites. The stimulation is applied via surface electrodes to drive the appropriate muscle to generate arm movements. The models of muscle activation dynamics and force production refer to sections 5.2.1 and 3.2.2.

More components are incorporated in the model comparing to the model described in section 5.2.1 and several new properties of musculoskeletal model are

Figure 5.8: Graphic representations of FES two-joints model. Seven muscles are included. To simplify, a hinge joint with no wrap-around insertions of muscles is used to describe the joint geometry. The condition of external loading is simulated by the spring and damping elements attached at the endpoint. θ_{el} and θ_{sh} is the elbow joint angle and glenohumeral (shoulder) joint angle, respectively. Counter-clockwise rotation is defined as positive. The range of motion of θ_{el} is from 0° (Extension) to 140° (Flexion), and that of θ_{sh} is from 50° (Transverse Flexion) to 180° (Transverse Extension). (Adapted from Luttgens and Hamilton [97]).

introduced. Such as new anatomical arrangement and coordinates of elbow and hand. Furthermore, in this study it is necessary to calculate the effects of external load again to adapt two-joints movement, which is also discussed in the later part of this section. Finally, since two muscles are added, the values of model parameters are modified based on literatures and listed in Table 5.1.

Anatomical arrangement:

Fig. 5.8 shows the anatomical arrangement of flexors and extensors at the elbow joint. A simple geometric representation of the elbow joint is used to calculate the properties of musculotendon complex, where the axis of rotation and each mus-

cle's attachment sites and path are approximated by a triangle [152]. Therefore, the moment arms of muscles can be calculated by the geometrically relationship as shown in Fig. 5.9.

To avoid the zero value of moment arms when $\theta_{el} = 0$, we set the minimum moment arms for each muscle, which is based on cadaver data [88] obtained using tendon displacement method. For the monoarticular flexor, extensor and Brachialis, the musculotendon length can be calculated as

$$\begin{aligned} L_{mf}^{MT} &= \sqrt{(L_{mf}^{ua})^2 + (L_{mf}^{fa})^2 + 2L_{mf}^{ua}L_{mf}^{fa}\cos\theta_{el}} \\ L_{me}^{MT} &= \sqrt{(L_{me}^{ua})^2 + (L_{me}^{fa})^2 - 2L_{me}^{ua}L_{me}^{fa}\cos\theta_{el}} \\ L_{bra}^{MT} &= \sqrt{(L_{bra}^{ua})^2 + (L_{bra}^{fa})^2 + 2L_{bra}^{ua}L_{bra}^{fa}\cos\theta_{el}} \end{aligned} \quad (5.11)$$

and the moment arms are,

$$\begin{aligned} h_{mf}^{el} &= \frac{L_{mf}^{ua}L_{mf}^{fa}\sin\theta_{el}}{L_{mf}^{MT}} \\ h_{me}^{el} &= \frac{L_{me}^{ua}L_{me}^{fa}\sin\theta_{el}}{L_{me}^{MT}} \\ h_{bra}^{el} &= \frac{L_{bra}^{ua}L_{bra}^{fa}\sin\theta_{el}}{L_{bra}^{MT}} \end{aligned} \quad (5.12)$$

For the biarticular flexor and extensor, we have,

$$\begin{aligned} L_{bf}^{MT} &= \sqrt{(L_{bf}^{fa})^2 + (L_1)^2 - 2L_1L_{bf}^{fa}\cos(\pi - \theta_{el} - \theta_1)} \\ L_{be}^{MT} &= \sqrt{(L_{be}^{fa})^2 + (L_2)^2 - 2L_2L_{be}^{fa}\cos(\theta_{el} - \theta_2)} \end{aligned} \quad (5.13)$$

and the moment arms to elbow are,

$$\begin{aligned} h_{bf}^{el} &= \frac{L_{bf}^{fa}L_1\sin(\pi - \theta_{el} - \theta_1)}{L_{bf}^{MT}} \\ h_{be}^{el} &= \frac{L_{be}^{fa}L_2\sin(\theta_{el} - \theta_2)}{L_{be}^{MT}} \end{aligned} \quad (5.14)$$

where

$$\begin{aligned} L_1 &= \sqrt{(L_{bf}^{sh})^2 + (L_{ua})^2 - 2L_{ua}L_{bf}^{sh}\cos\theta_{sh}} \\ L_2 &= \sqrt{(L_{be}^{sh})^2 + (L_{ua})^2 + 2L_{ua}L_{be}^{sh}\cos\theta_{sh}} \end{aligned}$$

5.9.a: geometrically relationship of monoarticular flexor and extensor of elbow

5.9.b: geometrically relationship of biarticular flexor and extensor of elbow

5.9.c: geometrically relationship of flexor and extensor of shoulder

Figure 5.9: Geometrically relationship of FES two-joints model.

and

$$\begin{aligned}\theta_1 &= \arcsin \left(\frac{L_{bf}^{sh} \sin \theta_{sh}}{L_1} \right) \\ \theta_2 &= \arcsin \left(\frac{L_{be}^{sh} \sin \theta_{sh}}{L_2} \right)\end{aligned}$$

the moment arms to shoulder are:

$$\begin{aligned}h_{bf}^{sh} &= \frac{L_{bf}^{sh} L_3 \sin(\theta_{sh} - \theta_3)}{L_{bf}^{MT}} \\ h_{be}^{sh} &= \frac{L_{be}^{sh} L_4 \sin(\pi - \theta_{sh} - \theta_4)}{L_{be}^{MT}}\end{aligned}\tag{5.15}$$

where

$$\begin{aligned}L_3 &= \sqrt{(L_{bf}^{fa})^2 + (L_{ua})^2 + 2L_{ua}L_{bf}^{fa} \cos \theta_{el}} \\ L_4 &= \sqrt{(L_{be}^{fa})^2 + (L_{ua})^2 - 2L_{ua}L_{be}^{fa} \cos \theta_{el}}\end{aligned}$$

and

$$\begin{aligned}\theta_3 &= \arcsin \left(\frac{L_{bf}^{fa} \sin \theta_{el}}{L_3} \right) \\ \theta_4 &= \arcsin \left(\frac{L_{be}^{fa} \sin \theta_{el}}{L_4} \right)\end{aligned}$$

For monoarticular muscles of shoulder:

$$\begin{aligned}L_{sf}^{MT} &= \sqrt{(L_{sf}^{ua})^2 + (L_{sf}^{sh})^2 - 2L_{sf}^{ua}L_{sf}^{sh} \cos \theta_{sh}} \\ L_{se}^{MT} &= \sqrt{(L_{se}^{ua})^2 + (L_{se}^{sh})^2 + 2L_{se}^{ua}L_{se}^{sh} \cos \theta_{sh}}\end{aligned}\tag{5.16}$$

and the moment arms are,

$$\begin{aligned}h_{sf}^{sh} &= \frac{L_{sf}^{ua}L_{sf}^{sh} \sin \theta_{sh}}{L_{sf}^{MT}} \\ h_{se}^{sh} &= \frac{L_{se}^{ua}L_{se}^{sh} \sin \theta_{sh}}{L_{se}^{MT}}\end{aligned}\tag{5.17}$$

Coordinates of elbow and hand

If we assume the shoulder is the origin point of coordinate system, and define the coordinate of elbow wrist is x_{el} , y_{el} , the coordinate of hand mass center is

x_{hand} , y_{hand} , thus we have:

$$x_{el} = -L^{ua} \cdot \cos \theta_{sh} \quad (5.18)$$

$$y_{el} = L^{ua} \cdot \sin \theta_{sh}$$

$$x_{hand} = -l_c \cdot \cos (\theta_{sh} - \theta_{x1}) \quad (5.19)$$

$$y_{hand} = l_c \cdot \sin (\theta_{sh} - \theta_{x1})$$

$$\text{where } l_c = \sqrt{(L^{fa} + 0.506 \cdot L_{hand})^2 + (L^{ua})^2 + 2 \cdot (L^{fa} + 0.506 \cdot L_{hand}) \cdot L^{ua} \cdot \cos \theta_{el}},$$

and

$$\theta_{x1} = \arccos\left(\frac{(L^{ua})^2 + l_c^2 - (L^{fa} + 0.506 \cdot L_{hand})^2}{2 \cdot L^{ua} \cdot l_c}\right), \quad 0 < \theta_{x1} < \pi$$

Correspondingly, we have,

$$\theta_{el} = \arccos\left(\frac{l_c^2 - (L^{fa} + 0.506 \cdot L_{hand})^2 - (L^{ua})^2}{2 \cdot (L^{fa} + 0.506 \cdot L_{hand}) \cdot L^{ua}}\right) \quad (5.20)$$

$$\theta_{sh} = \theta_{x1} + \theta_{x2}$$

where, $l_c = \sqrt{x^2 + y^2}$ and

$$\theta_{x2} = \begin{cases} \arctan\left(\frac{y}{-x}\right), & x \leq 0 \\ \pi - \arctan\left(\frac{y}{x}\right), & x > 0 \end{cases}$$

with $0 < \theta_{x2} < \pi$.

External load:

The external force is applied along the line between the fix point (x_{sp}, y_{sp}) and the mass center of hand (x_{hand}, y_{hand}) during arm flexion (See Fig. 5.10). The force is performed as a pulse perturbation provided by a spring (slack length L_s^{sp} , stiffness k_L). The torque caused by the external force is calculated as following:

If the force provided by a spring, the spring length L^{sp} is

$$L^{sp} = \sqrt{(x_{sp} - x_{hand})^2 + (y_{sp} - y_{hand})^2}$$

Figure 5.10: The external force provided by spring or the pulse perturbation for FES two-joints model

The moment arm of external force to elbow joint h_{el}^{sp} is

$$h_{el}^{sp} = l_{elbow-sp} \cdot \sin(\alpha_{elbow-sp-hand})$$

to shoulder joint h_{sh}^{sp} is

$$h_{sh}^{sp} = l_{sh-sp} \cdot \sin(\alpha_{sh-sp-hand})$$

Thus, the dynamic external torque to elbow joint is given as,

$$T_L^{el} = \begin{cases} k_L \cdot (L^{sp} - L_s^{sp}) \cdot h_{el}^{sp}, & L^{sp} \geq L_s^{sp} \\ 0 & L^{sp} < L_s^{sp} \end{cases} \quad (5.21)$$

and, this to shoulder joint is,

$$T_L^{sh} = \begin{cases} k_L \cdot (L^{sp} - L_s^{sp}) \cdot h_{sh}^{sp}, & L^{sp} \geq L_s^{sp} \\ 0 & L^{sp} < L_s^{sp} \end{cases} \quad (5.22)$$

where

$$l_{elbow-sp} = \sqrt{(x_{sp} - x_{el})^2 + (y_{sp} - y_{el})^2}$$

$$l_{sh-sp} = \sqrt{(x_{sp})^2 + (y_{sp})^2}$$

$$l_{sh-hand} = \sqrt{(x_{hand})^2 + (y_{hand})^2}$$

$$\alpha_{sh-sp-hand} = \arccos\left(\frac{(L^{sp})^2 + l_{sh-sp}^2 - l_{sh-hand}^2}{2 \cdot L^{sp} \cdot l_{sh-sp}}\right), \quad 0 < \alpha_{sh-sp-hand} < \pi$$

$$\alpha_{elbow-sp-hand} = \arccos\left(\frac{(L^{sp})^2 + l_{elbow-sp}^2 - (L^{fa} + 0.506 \cdot L_{hand})^2}{2 \cdot L^{sp} \cdot l_{elbow-sp}}\right), \quad 0 < \alpha_{sh-sp-hand} < \pi$$

Model parameters:

Table 5.1 presents the values of model parameters for simulation study, which is derived from *in vivo* ultrasonograohy, anthropometry and literatures (refer to section 3.3).

Table 5.1: Model parameters ^a

Activation dynamics		Contraction dynamics				Anatomical arrangement and Joint dynamics		Tendon compliance	
		Muscle specific		Muscle nonspecific					
W_d (s)	0.000122	F_{max-mf} (N) ^b	118.9	a	1.5	L_{mf}^{fa} (m)	0.065	k_{mf}^T (N/m)	42919
W_s (s)	0.000487	F_{max-me} (N)	321.6	b	8.0	L_{me}^{fa} (m)	0.04	k_{me}^T (N/m)	46307
τ_{rise} (s)	0.02	F_{max-bf} (N)	112.1	c	0.0866	L_{bf}^{ua} (m)	0.28	k_{bf}^T (N/m)	41784
τ_{fall} (s)	0.06	F_{max-be} (N)	160.5	d	-3.188	L_{me}^{ua} (m)	0.22	k_{be}^T (N/m)	37888
k_f (s)	0.1	$F_{max-bra}$ (N)	257.4	c^{PE1}	23	L_{bra}^{fa} (m)	0.025	k_{bra}^T (N/m)	71467
p_{min}	0	F_{max-sf} (N)	170.3	k^{PE1}	0.046	L_{bra}^{ua} (m)	0.15	k_{sf}^T (N/m)	138922
τ_{fat} (s)	18	F_{max-se} (N)	149.2	L^{PE1}	1.17	L_{bf}^{fa} (m)	0.065	k_{se}^T (N/m)	81128
τ_{rec} (s)	30	L_{o-mf}^M (m) ^c	0.150	η	0.01	L_{be}^{fa} (m)	0.04	L_{s-mf}^T (m)	0.18
β	0.6	L_{o-me}^M (m) ^d	0.114	c^{PE2}	-0.02	L_{bf}^{sh} (m)	0.03	L_{s-me}^T (m)	0.1118
		L_{o-bf}^M (m)	0.177	k^{PE2}	-21.0375	L_{be}^{sh} (m)	0.028	L_{s-bf}^T (m)	0.2003
		L_{o-be}^M (m)	0.143	L^{PE2}	0.70222	L_{sf}^{ua} (m)	0.08732	L_{s-be}^T (m)	0.1678
		L_{o-bra}^M (m)	0.092			L_{se}^{ua} (m)	0.16	L_{s-bra}^T (m)	0.0738
		L_{o-sf}^M (m)	0.119			L_{sf}^{sh} (m)	0.12	L_{s-sf}^T (m)	0.04
		L_{o-se}^M (m)	0.142			L_{se}^{sh} (m)	0.03	L_{s-se}^T (m)	0.06
						L^{ua} (m) ^e	0.30		
						L^{fa} (m) ^f	0.25		
						L_{hand} (m) ^g	0.13		
						M (kg)	68		
						I_{el} (kg * m ²)	0.0601		
						I_{sh} (kg * m ²)	0.2450		

^a The data obtained from ultrasound measurement for a male subject and literatures [4–7,90].

^b $F_{max} = \text{PCSA}(\text{m}^2) * 330(\text{kpa})$.

^c Defined as the optimal muscle fascicle length (the length of a small bundle of muscle fibers from the tendon of origin to the tendon of insertion) [5]

^d value of L_{o-me}^M is chosen as the optimal fascicle length of the lateral head.

^e Defined as the distance between glenohumeral joint and elbow joint.

^f Defined as the distance between elbow joint and ulnar styloid.

^g Defined as the distance between wrist joint and knuckle II of middle finger.

Control scheme

The threshold FES controller proposed in section 5.2.1 organizes merely the antagonist muscles around one hinge joint. To coordinate the action of two joints, the seven muscles are divided into three groups of antagonist muscles based on their functions: the mono-articular elbow muscle group (Muscles 1, 2 and 3), the biarticular muscle group (Muscles 4 and 5) and the mono-articular shoulder muscle group (Muscles 6 and 7). Two mono-articular muscle groups are controlled by two separate FES controllers, which integrate the corresponding input commands and feedbacks from joints to generate the stimulation pattern. The stimulation pattern of the biarticular muscle group is assumed to be as same as that of the mono-articular elbow muscle group. This assumption is based on two perspectives: 1) The biarticular muscle and the mono-articular muscle of elbow joint belong to the same anatomical muscle group, thus it is difficult to stimulate them separately by surface electrodes. 2) Previous simulation study suggested that biarticular muscles affected the stability of elbow joint more effectively than that of shoulder joint because the moment arms of the biceps and triceps muscles at the elbow joint are greater than those of shoulder joint [90]. The flowchart of FES control system for two joints movement is shown in Fig. 5.11.

5.3.2 Simulation results

The designed controller is applied to drive right hand to move from right hand side to left hand side with the desired trajectory in horizontal plane. The trajectory is defined as the path of the hand mass center. The simulation results of the model with different feedback delays are shown in Fig. 5.12. The parameters for simulation are listed in Table 5.1. Figs. 5.12.a, 5.12.b and 5.12.d show the

Figure 5.11: The flowchart of FES control system for 7 muscles, two joints movement.

simulated trajectory of the hand in horizon plane and the time course of elbow and shoulder angle, respectively. Figs. 5.12.c and 5.12.e show the tracking errors of the joint angles Vs. time. To quantify the performance of the model, the root-mean-squared (RMS) values between simulated and desired trajectory is calculated and listed in the annotation of Fig. 5.12. The time shift between the two trajectories is eliminated before calculating the value of RMS. The small value of RMS suggests that the system can approximatively follow the trajectory to achieve the desired task. Fig. 5.12.a shows the trajectory in X-Y (horizon) plane. The corresponding elbow and shoulder joint angle trajectory are presented in Figs. 5.12.b and 5.12.d, respectively. The tracking error of elbow and shoulder movement are shown in Figs. 5.12.c and 5.12.e, respectively. In detail, the RMS values of elbow joint angle are: 0.7435° ($t_d = 0$ ms), 1.0529° ($t_d = 10$ ms), 1.6103° ($t_d = 20$ ms). RMS values of shoulder joint angle are: 2.1044° ($t_d = 0$ ms), 2.0888° ($t_d = 10$ ms),

2.2892° ($t_d = 20$ ms). The following characteristics can be observed from the simulation results: 1) the system is stable with different feedback delays and can realize the movement along the desired trajectory, even without re-optimizing the parameters of the controller. 2) the speed of simulated movement is slower than the desired speed. This results from the responding delay of the musculoskeletal system, and can be partially compensated by increasing the rates of R commands. The difference between the simulated and desired trajectory of the shoulder joint is relatively more severe than that of the elbow joint. This is because the moment arms of flexor and extensor muscles of shoulder joint are relatively shorter and the moment of inertia of shoulder joint is relatively bigger. These anatomical differences cause the slower response of the shoulder joint to a stimulus. 3) as the feedback delay increases, the values of RMS increase as well as the overshoot that occurred in the final position. It implies that the threshold controller can only stabilize the system within the limited delays.

Next, the performance of system with the external load is studied. The external force is added along the line between the point (pentagram, x:0.5, y:0.6) and the mass center of hand. The torque caused by the external force is determined by the trigonometric functions presented in section 5.3.1. The dynamic response of the system in the presence of the pulse perturbations is shown in Fig. 5.13. Simulation results suggest that even strong pulse perturbations (150 N during 10 ms,) do not impair the system stability during the movement (Fig. 5.13.a and 5.13.b) or at the final position (Fig. 5.13.c and 5.13.d). Fig. 5.14 shows the system performance when a continuous external load is applied to the hand. The continuous external force is produced by a light spring. The spring is fixed between the point (x:0.5, y:0.6) and the mass center of hand. The stiffness of spring k_L is 5 N/m, the slack length L_s^{sp} is 0.4 m. The simulation results demonstrate successful

5.12.a: Trajectory

5.12.b: Elbow Angle

5.12.c: Elbow Angle Tracking Error

5.12.d: Shoulder Angle

5.12.e: Shoulder Angle Tracking Error

Figure 5.12: The simulation results of the FES controlled two joints movement with different feedback delays. The desired trajectories (R commands), the C commands and the system outputs are represented by dashed lines, dotted lines and solid lines, respectively. The feedback gains are fixed. ($\mu_{el} = 0.12$ s, $k_{\xi-el} = 0.005$ s², $\mu_{sh} = 0.6$ s, $k_{\xi-sh} = 0.015$ s²).

adaptation of the controller to the change of external load. Though there are small differences between the simulated and desired endpoint, the system still can generate a stable outcome. It suggests that in order to compensate the influence of the external load, the R command should be adjusted based on the desired trajectory.

5.4 Discussion

In this chapter, the physiology-based threshold control scheme is employed in the FES controller for the first time. The simulation results suggest that the feedback information from joint angular sensors (e.g., joint angle, joint angular velocity and acceleration) is crucial for the controller to achieve the desired task. In the aspect of control theory, the threshold FES controller is a hybrid controller combining the close-loop proportional-derivative (PD) control and open-loop co-activation control.

The open-loop components (Fig.5.3 without feedback) represent internal static properties of the musculoskeletal system. In essence, the implemented co-activation controller provides a map relating desired trajectory (R commands) to the open-loop stimulation. The co-activation C commands can accelerate movement generation. If the controller precisely generates the appropriate muscle stimulation, the actual joint angle will match the desired angle. In such a condition, the C command will be the only control input to generate the muscle stimulation. However, as a result of the complexity of the musculoskeletal system, a “pure” open-loop co-activation controller (such as α -controller in voluntary motor control [12]) is incapable of generating the proper movement to match the desire trajectory. Besides the universal shortcoming of the open-loop controller, the co-activation controller

5.13.a: Trajectory with perturbation during movement

5.13.b: Joint Angle with perturbation during movement

5.13.c: Trajectory with perturbation after the offset of movement

5.13.d: Joint Angle with perturbation after the offset of movement

Figure 5.13: Responses of FES two-joints model to external perturbations in the presence of feedback delays of 20 ms. Dashed lines represent desired trajectory (R commands), dotted lines represent C commands and solid lines represent output of the systems. Fig. 5.13.a and 5.13.b show the hand trajectory and joint angle output with perturbation at the process of movement (*arrow*, starting 0.7 s, 150 N, during 10 ms), respectively. Figs. 5.13.c and 5.13.d show the hand trajectory and joint angle output with perturbation after the offset of movements (*arrow*, starting 2.5 s, 150 N, during 10 ms), respectively.

5.14.a: Trajectory with External Load

5.14.b: Joint Angle with External Load

5.14.c: External Torque

Figure 5.14: Responses of FES two-joints model to external loads in the presence of feedback delays of 20 ms. Dashed lines represent desired trajectory (R commands), dotted lines represent C commands and solid lines represent output of the systems. The external load is produced by a spring fixed between the pentagram ($x:0.5$, $y:0.6$) and the mass center of hand. Figs. 5.14.a and 5.14.b show the hand trajectory and joint angle output, respectively. Fig. 5.14.c shows the time course of external torques acted in the elbow and shoulder joint.

can not generate movement as fast as the desire task, because the speeds generated by the co-activation controller strongly depend on the local stiffness of the prescribed equilibrium point (EP). The stiffness in an EP can be deemed as an internal property of the musculoskeletal system, which is defined as “the change of steady-state net torque for a given deviation from that EP” [11].

On the other hand, though the PD controller can reject the disturbance perfectly when muscles produce proper force on time, it is insufficient to generate stable movement if the feedback delay is too long. This phenomenon can be explained as following: since the muscle activations generated by PD controller are only resulted from feedback, if the feedback is postponed, instability and oscillatory will occur when the PD controller try to regulate stimuli to compensate the detected errors. From the viewpoint of patient safety and control accuracy, such a condition is undesirable for FES applications.

The threshold FES controller combines the advantages of the open-loop and close-loop controller, hence partially prevents time-lag-instability. Furthermore, additional reciprocal inhibition is introduced to the threshold controller to increase the responding time. It is expected that the proposed controller is robust to the change of musculoskeletal structure, i.e., values of controller variables are not sensitive to the the inertial parameters of the musculoskeletal system. Some additional simulations are done to explore the effect of parameter values on system performance. It is noticeable that paralyzed patients vary with ages, thus it is meaningful to test that whether the controller can be applied to both young and old adults without adjusting control parameters. Since the parameters listed in Table 5.1 are captured from young adults, we adjust them based on literatures to simulate the status of old adults. In detail, 1) maximum isometric muscle forces is reduced (F_{max}^M is reduced 30%); 2) maximum contraction velocity is decreased

(V_{max}^M is reduced 20%); 3) passive muscle stiffness is increased (c_{PE1} and c_{PE2} is increased 20%); 4) the relaxation time is increased (τ_{fall} is increased 20%) [109]. To quantify the change in performance, the RMS values between the simulated and desired traces (elbow joint: $\text{RMS-}\theta_{el}$; shoulder joint: $\text{RMS-}\theta_{sh}$) and the peak angular velocity of joint (elbow joint: ω_{el}^{peak} ; shoulder joint: ω_{sh}^{peak}) are calculated. It is found that the changes in these parameters led to the small increase in RMS values and decrease in the peak angular velocity (see Table 5.2), but the outcome of system is stable and approximately follows the desired trajectory. Furthermore, to test the sensitivity of the simulation outcome to the change in C commands, the simulation is performed with doubled C commands. It is found that the performance of the model is not impaired (see Table 5.2). These results suggest that threshold FES controller is robust to musculo-tendon property changes due to aging.

Another noticeable model parameter affecting the system outcome is the feedback time delay, which diminishes the usefulness of feedback. The previous simulation results had suggested that the deviation between the desired and simulated trajectory are not significantly affected by the increase of feedback delay. We further test the model performance with feedback delay $t_d=0, 10$ and 20 ms for the young and old adults. Simulation results show that whether young or old adults, a longer delay will cause an increase in the RMS values, but the peak angular velocity is not significantly changed (see Table 5.2). This demonstrates that the threshold controller has the capability of producing the desired task even when different latencies in the feedback loop are employed.

Table 5.2: Sensitivity of simulation results to changes in model parameters *

	ω_{el}^{peak} (deg/s)	RMS- θ_{el} (deg)	ω_{sh}^{peak} (deg/s)	RMS- θ_{sh} (deg)
Youth ($t_d=0$ ms)	318.76	0.7435	187.44	2.1044
Youth ($t_d=10$ ms)	328.31	1.0529	189.91	2.0888
Youth ($t_d=20$ ms)	339.46	1.6103	193.40	2.2892
Old ($t_d=0$ ms)	271.35	1.2864	142.50	3.3868
Old ($t_d=10$ ms)	276.72	1.4181	144.69	3.3643
Old ($t_d=20$ ms)	282.76	1.5718	147.48	3.3758
Young (C*2, $t_d=20$ ms)	349.03	1.5694	191.24	2.3018
Old (C*2, $t_d=20$ ms)	289.78	1.9641	146.34	3.3511

* R and C commands are shown in Fig.5.12.b and 5.12.d except Young (C*2, $t_d=20$ ms) and Old (C*2, $t_d=20$ ms), in which the C commands are doubled. the feedback gains are optimized under the condition of young adults with feedback delay $t_d=20$ ms. The parameters of musculoskeletal model for young adults are listed in Table 3.2. The musculo-tendon parameters of old person are adjusted from those of young adults. The other parameters stay with the same.

To sum up, these results suggest that the performance of the threshold FES controller is not critically depend on the representation of the musculo-tendon parameters. The controller can realize the task with the range of feedback delay caused by the sensors. Comparing with the existing FES controller, the proposed controller is more superior in the following aspects: 1) ability to control redundant musculoskeletal system without solving the inverse model and cost function; 2) flexibility to adapt the change of musculoskeletal parameters and feedback delays without adjusting the controller parameters.

Though only simulation studies are performed in this chapter, our work provides a promising technique for the clinical application. The threshold FES controller is not only a physiology-based controller but also a controller adopting many traditionally mature control techniques, such as PID control and open-loop control. In summary: 1) the controller can be easily implemented in hardware; 2)

only simple sensors are required for acquiring the feedback information (i.e., goniometer); 3) the surface electrodes are sufficient for the FES control system, as the movement is realized without stimulating individual muscle.

5.5 Conclusion

The aim of this chapter is to develop a novel FES control system for the paralyzed patient arm. Three FES controllers are developed based on the physiology-based threshold control theory. Simulation results prove that the all threshold FES controllers adequately stabilizes musculoskeletal systems and realizes the desired task. By contrast, the Acc. FES controller depicted in equations 5.8, 5.9 and 5.10 has the best performance in the sense of stability and movement error. Our study hints that FES-driven human movement can be controlled without the requirement of solving the “inverse dynamics problem”.

Further simulation studies are conducted to explore the sensitivity of the system performance to changes in model parameters and feedback delays. The results suggest that the controller is robust for 1) small changes in feedback delays; 2) small deviations in the applied feedback gains and input commands; 3) the slight changes of the musculo-tendon parameters.

Chapter 6

FES Control for Two-dimensional Human Walking by Threshold Controller and Central Pattern Generator

6.1 Introduction

Design of FES walking controller is difficult due to the complexity of walking. To build such a controller, many researchers had tried to apply the physiological neural control mechanism to engineering application. However how the human motor control system realizes human walking is still an open question. In this chapter, we present a possible control strategy to investigate this mechanism, and

apply this strategy for FES walking control.

In the previous chapters, the validity of threshold control theory (chapter 4) and the applicability of threshold based FES controller (chapter 5) had been proved by experimental and simulation studies. Next we intend to apply this theory to more complex movement, such as human walking. The same theory had been used by other research groups to simulate human walking, however, CPG was not considered to be essential. For example, Güther et al. constructed an integrated neuro-musculoskeletal circuit based on λ -model and claimed that the rhythmic motor pattern can be produced by this circuit [8]. In their study, the time characteristics of the walking pattern is determined by the proprioceptive afferent interacting with the central neural system. They suggested that the central pattern generator (CPG) is not necessary for coordinating walking. Some other studies also suggest that the motor control system based on CPG can not solve the posture-movement problems in the absence of sensory feedback [26].

However, we can not completely neglect the function of CPG when modeling human motor control system. It had been observed that CPG can realize simple movements. For example, the deafferentation experiments clearly showed that some movements can be generated in the absence of proprioceptive signals [9, 10]. Thus we intend to incorporate CPG into threshold control theory to develop a bio-mimic artificial controller for human walking. In detail, CPG generates a static reference frame of movements. The static threshold is transformed into a dynamic threshold by introducing proper proprioceptor feedback signals. The FES stimulation is determined by the difference between the actual muscle length and the desired threshold. To test the feasibility of the designed control scheme, a two-dimensional, 7 segments musculoskeletal model of the human body is proposed in this chapter, which includes 9 muscles per leg. The human walking is generated by the combination of the coupled muscles and rigid body dynamics.

To illustrate the contribution of threshold control theory within the proposed controller(CPG-threshold controller), the model that is purely controlled by CPG is also presented (CPG-controller). The performances of two models are compared.

This chapter is organized as following: the model description is given in section 6.2. In detail, the summary of the walking musculoskeletal system is shown in section 6.2.1. The structure of CPG is presented in section 6.2.2. The details of FES controllers used in this chapter is presented in section 6.2.3. The simulation results are presented in section 6.3. Finally, the discussion and conclusion are given in sections 6.4 and 6.5.

6.2 System description

The block diagram of the proposed CPG-threshold controller for human walking is shown in Fig. 6.1. In this model, the walking movement is controlled by the control algorithms derived from threshold control theory and CPG. The supraspinal system is assumed to provide basic “ON/OFF” motor command to initiate CPG, and CPG provides the rhythmic control signal for walking. The CPG generate the rhythmic signal y^r for each muscle. The frequency of rhythmic signal is determined by the speed gain K_f . y^r is normalized to the interval [0,1]. It is noted that CPG exchanges the roles of legs as swing leg or stance leg during walking. In another word, it switches the walking pattern between contact task and non-contact task. For the CPG-controller, these signals are directly used as the FES stimulations. For the CPG-threshold model, these signals are used as the static thresholds λ for the λ controller. The static threshold will be transformed to dynamic threshold λ^* by integrating the feedback of muscle contraction velocity V .

Then, the FES stimulation E is determined by the difference between the actual muscle length L and dynamical threshold λ^* .

At the same time, the posture controller keeps the human body from collapsing during the stand phase. The task is realized by maintaining the center of gravity (COG) within the stable region. The inputs of the controller are the joint angle and angular velocity. The outputs are the posture factors, which are multiplied by the FES stimulation to adjust the output of muscle force [86]. However, to compare the performance of CPG-controller and CPG-threshold controller, the same posture factor is used in these two models.

The muscle activation dynamics is described in section 5.2.1. For simplicity, it is assumed that the fatigue factor is equal to 1, and the time-delay caused by the conduction and chemical reaction in membrane system is not included. The contraction dynamics is described in section 3.2.2.

6.2.1 Musculoskeletal system

The two-dimensional mechanical model consists of 7 segments and 18 muscles (Fig. 6.2). The body is modeled as one head-arms-trunk (HAT) segment plus two legs, each leg has a thigh, a shank, and a foot. The segments are connected by hinge joints and driven by muscles. Since the two legs are symmetric, without lose of generality, only nine muscles of one leg (right leg) are illustrated in this study. The muscle are modeled as a Hill-type unit consisting of a contractile element (CE), a parallel elastic element (PE), and a series elastic element (SEE). The details of the muscle model have been elaborated in chapter 3. The skeletal dynamics (joint dynamics in section 3.2.5) of the human body are estimated using Newton-Euler method [87, 153], i.e.,

6.1.a: CPG-controller

6.1.b: CPG-threshold controller

Figure 6.1: Block diagram of the proposed FES controlled models for human locomotion. Note that the CPG-threshold controller can be changed to CPG-controller if the normalized CPG output is directed used as the electrical stimulation pattern.

Figure 6.2: Musculoskeletal model of human walking. θ_h , θ_k and θ_a are joint angles of hip, knee and ankle, respectively.

$$T + M(\theta)\ddot{\theta} + C(\theta, \dot{\theta}) + G(\theta) + T_L(\theta) = 0 \quad (6.1)$$

Where θ is the vector of the joint angles. T is the vector of musculotendon torques acted on the joints. $T_L(\theta)$ is the vector of torques acted on joint due to other external forces besides gravity, which includes the disturbance torque and ground torque applied to the foot in this case. $M(\theta)$ is the inertial matrix. $C(\theta, \dot{\theta})$ is the vector of centrifugal and Coriolis torque. $G(\theta)$ is the vector of gravitational torque. The details of motion equations are refer to Appendix. Anthropometric parameter values of the muscle model and the skeletal dynamics are adopted from the literatures [145, 154].

Each leg experiences stance and swing phases during a gait cycle. In the stance phase, the ground reaction force (GRF) is generated to foot. Two aspects

Figure 6.3: Bio-mechanical model of foot with action to ground.

are considered in modeling of foot-ground contact: geometry of the foot, and force-deformation characteristics of the foot sole or shoes. To reduce the complexity of computation, it is assumed that the foot is the rigid body. The interaction of foot and ground is modeled as the viscoelastic elements, i.e., dampers and springs. The mechanical structure is shown in Fig. 6.3. For horizontal, the viscosity and elasticity coefficients of foot are set as 200N/m and 5000N/m, respectively; for vertical, the coefficients are set as 500N/m and 25000N/m, respectively [154]. The GRF is determined by the product of the viscoelastic element coefficients and the foot horizontal/vertical displacement during stance state.

6.2.2 Central pattern generator

In this study, CPG is used to generate FES stimulation patterns (CPG-controller) or muscle threshold lengths (CPG-threshold controller) for rhythmic movements with desired frequencies and phases. To generate rhythmic patterns for the muscles related to three joints of each leg: hip, knee and ankle, three pairs of oscillators are designed (Fig. 6.4). i.e , the CPG consists of six pairs of oscillators for both legs. Each oscillator includes two coupled neurons with self and mutual inhibition. It can be described by the following ordinary differential

equations [154]:

$$\frac{\tau_{i1}\dot{x}_{i1}}{K_f} = -x_{i1} - \beta_i\nu_{i1} - h_i\dot{y}_{i2} - \sum_{j=1, j \neq i}^6 (p_{ij-1} * \dot{y}_{j1} + q_{ij-1} * \dot{y}_{j2}) \quad (6.2)$$

$$\tau_{i2}\dot{\nu}_{i1} = -\nu_{i1} + \dot{y}_{i1} \quad (6.3)$$

$$\frac{\tau_{i1}\dot{x}_{i2}}{K_f} = -x_{i2} - \beta_i\nu_{i2} - h_i\dot{y}_{i1} - \sum_{j=1, j \neq i}^6 (p_{ij-2} * \dot{y}_{j1} + q_{ij-2} * \dot{y}_{j2}) \quad (6.4)$$

$$\tau_{i2}\dot{\nu}_{i2} = -\nu_{i2} + \dot{y}_{i2} \quad (6.5)$$

$$\dot{y}_{i1} = \max(x_{i1}, 0), \quad \dot{y}_{i2} = \max(x_{i2}, 0) \quad (6.6)$$

where $i = 1, 2, 3$ is the index for hip oscillator, knee oscillator, and ankle oscillator, respectively. Two neurons x_{i1} and x_{i2} of the i th oscillator represent the two states of the oscillator. τ_{i1} and τ_{i2} are time constants. β_i and h_i are the weights for the connections among the neural oscillators; p_{ij-1} , q_{ij-1} , p_{ij-2} and q_{ij-2} are the weights of the connections between the neural oscillators. j indicates the index of the weights. $\dot{y}_{i1,2}$ is the outputs of the CPG. For the simpler description, we rename the CPG outputs: $y_1 = \dot{y}_{11}$, $y_2 = \dot{y}_{12}$, $y_3 = \dot{y}_{21}$, $y_4 = \dot{y}_{22}$, $y_5 = \dot{y}_{31}$, $y_6 = \dot{y}_{32}$. K_f is the speed gain, which can adjust the rhythm frequency (see in Fig. 6.9).

As shown in Fig. 6.4, the CPG for the walking control is a fully connected system [86]. The relationship between the rhythmic signal and neuron outputs is determined by the anatomical function of muscles. For example, the rhythmic signal for the hip extensor and flexor are determined by the outputs from the two neurons in the hip oscillator. i.e., $y_1^r = y_1$. Similarly, the muscles of the knee joint and ankle joint are stimulated by the knee oscillator and ankle oscillator, respectively. In detail, the rhythmic signals of the biarticular muscles (RF, HAM, GAS) are provided by two neurons, because these muscles cross two joints and serve as the flexor of one joint and the extensor of the other joint in the same time. For example, RF influences the joint torque of the hip and knee joints during

Figure 6.4: The structure of CPG for walking control (adapted from [154]). Two CPGs are constructed for two legs. Only the details of right leg are presented, because the CPGs for two legs are symmetric. The parameter K_f determine the speed of walking. The dashed lines represent weak connection.

the gait cycle. Therefore, the hip flexor neuron (neuron 1) and knee extensor neuron (neuron 3) are combined to provide the rhythmic signals for the RF. The relationship is defined as $y_7^r = c_2 y_1 + c_3 y_3$, where c_2 and c_3 are the coefficients. It is noted that the values of y^r are normalized to the interval $[0,1]$ by the maximum values. y^r is used differently in different models. In detail, it is used as the muscle thresholds in CPG-threshold controller, while it is used as the FES stimulation pattern in CPG-controller. The pattern of CPG for generating the human gait are shown in Fig. 6.5. The detailed properties and discussion is presented in Zhang et al. [155].

6.2.3 Threshold controller

The implemented threshold controller is adopted from the equation discussed in chapter 5. The formulations at the single muscle level are used,

$$\begin{aligned} \lambda^* &= \lambda - \mu V(t - t_d) \\ E &= [\lambda^* - L(t - t_d)]_0^1 \end{aligned} \tag{6.7}$$

Figure 6.5: The output from CPG with 1 Hz rhythmic motor pattern.

where E is the FES stimulation pattern. λ is the static threshold length of the muscles, which is generated by CPG. λ^* is the dynamic threshold. L is the normalized muscle fascicle length to the optimal muscle fiber length. V represents the normalized muscle contraction velocity to the maximum shortening velocity of the muscle. The feedback gain μ is optimized to minimize the differences between simulated and experimental movements (derived from reported experimental measurements [154, 156]). The optimal values are identified using a radial basis function neural network. $t_d=30$ ms is the feedback time delay.

6.3 Simulation results

In this study, two models (CPG-controller and CPG-threshold controller) are evaluated. It is noted that the CPG-controller is an open-loop model, thus the problem of feedback delay does not exist in the CPG-controller.

A fixed step-size (step-size:10 ms) ordinary differential equation solver based

on the Bogacki-Shampine formula is used to numerically solve the equations of the neuro-musculoskeletal model. Model and simulations are implemented in Matlab 7.1 (R14) and Simulink. The parameters of the CPG are tuned according to empirical and analytic methods [157–159].

6.3.1 CPG-controller

The joint angle outputs of the CPG-controller are shown in Fig. 6.6. Though the musculoskeletal model can generate the rhythmic movement with only CPG controller, the shape of joint curves is quite different from the natural human walking (compared with the experimental records shown in Fig. 6.7). For example, the joint angles (ankle, knee, hip) exceed the range in which the posture is maintained. This results suggest that CPG can not provide a reliable FES stimulation pattern without the adjustment of feedback signals. The simulation results agree with the previous results of deafferentation experiments. i.e, even after long-term training, deafferented patients can not walk without assistance [160].

6.3.2 CPG-threshold controller

The performance of CPG-threshold controller is presented in this section. The time series of joint angles are shown in Fig. 6.7 and the correlative FES stimulation patterns are shown in Fig. 6.8. To illustrate the performance, the experimentally recorded trajectories are also shown in Fig. 6.7. The same CPG parameters that are previously used in CPG-controller are adopted in CPG-threshold controller. The following conclusions can be derived from the simulation results: 1) The frequency of walking is the same with the CPG-controller and CPG-threshold controller. This suggests that the rhythmic motor pattern is not influenced by

Figure 6.6: Simulated joint angles of right limbs during walking by CPG-controller with 1 Hz rhythmic motor pattern.

threshold controller; 2) The angle output of CPG-threshold controller is closer to the natural walking pattern than that of the CPG-controller. That means that the amplitude and the pattern of the joint angle are adjusted by the threshold controller to match the natural movements. To sum up, CPG-threshold controller can produce satisfactory FES stimulation patterns and sequence to activate muscles for walking.

6.3.3 Speed control

Based on the flow chart of Fig. 6.1, a varying speed of walking can be achieved by adjusting the speed gain K_f . The adjustment of K_f changes the rhythm of the leg movement. The time series of joint angles during locomotion and the corresponding values of K_f are shown in Fig. 6.9. It is noted that the maximum values of knee angle vary with K_f . When the K_f increases (speed increases), the controller has to compensate the feedback error in greater extent, as the responding

6.7.a: Hip

6.7.b: Knee

6.7.c: Ankle

Figure 6.7: Simulated joint angles of the CPG-lambda model with 1 Hz rhythmic motor pattern, feedback delay $t_d = 30\text{ms}$. Experimental records is described as solid line, simulation results is presented as dash line.

Figure 6.8: Simulated stimulation patterns with CPG-threshold controller.

time is shortened due to the fixed feedback time. This strong compensation results in the increase of the maximum knee angle. Furthermore, the knee angle of the fast movement is larger than that of slow movement. This is consistent with the natural phenomenon that the stride length of human increases as the walking speed increases.

6.3.4 Perturbation

To test the ability of the CPG-threshold controller to resist mechanical disturbance, we tested the dynamic response of the system when one leg is stumbled by an unexpected obstacle. In the simulation study, a strong impulse (three times larger than normal torque) is applied to each joint. The good robustness under this case is demonstrated by the simulation results shown in Fig. 6.10. It suggests that the joint angles return to the original trajectory after a vibration for less than 0.4 s.

Figure 6.9: Variation of locomotion speed. The feedback gain μ is optimized to the situation of $K_f = 1$.

Figure 6.10: Performance of CPG-threshold controller with external perturbation. Feedback delay $t_d = 30$ ms

6.4 Discussion and conclusion

6.4.1 Physiological roles of CPG and the threshold

controller

The simulation results suggest our proposed model fits better with experimental observations (the walking of deafferented patients with assistance), compared to the previous study of λ -model [8]. This suggests that the proposed CPG-threshold controller is closer to the natural controller. Thus it may reveal the possible functions of CPG and threshold-control module. In details, 1) CPG generates the basic pattern for each muscle; 2) threshold-control module transforms the basic pattern to the executable file with the sensory feedback.

Based on the threshold control theory, the muscle excitation depends on the difference between the muscle length and the desired thresholds. We assume that the normalized threshold muscle lengths are defined by CPG. Such an assumption means that CPG plays a role of “decision-maker” in the whole system, i.e., it generates the basic pattern for each muscle only with a simple “ON/OFF” signal sent from brain. On the contrary, the threshold-control module is a “coordinator”, who transforms the rough command to the executable file with the feedback information. If only CPG is activated, the motor system will generate a rhythmic but unstable movement. If only threshold control model works, we have to define a series of thresholds in order to drive the controller, as Güther et al. had done before. To sum up, human motor control system for human walking might be modeled as a CPG-driven threshold controller. Considering the fact that infants need to learn walking, it is suggested that the infants only has a basic CPG to generate simple rhythm, the development of the muscle excitation pattern need long-term training during the interactions with environment.

6.4.2 Rhythmic movement and monotonic movement

In the previous studies, the rhythmic movement had been realized by a controller based on the combination of CPG and threshold control theory. However, the potential of CPG-threshold controller is not confined to rhythmic movement. After elaborate tuning, it can also produce monotonic movement if following conditions for a single CPG oscillator are guaranteed (refer to Zhang [154]):

$$\beta \leq h - 1, \quad \text{or,}$$

$$h \leq 1 + \frac{\tau_1}{\tau_2}, \quad \text{or,}$$

$$r = 0.$$

In another word, if above conditions are satisfied, the output of oscillator will converge to a unique equilibrium value. The resulting controller is equivalent to the threshold controller presented in chapter 5.

6.4.3 Speed control

Based on the investigation of Güther, walking speed is controlled by a series of feedback gains. These gains are identified from the successful simulations by trial-and-error method. On the contrary, in this study, the walk speed is only determined by a single control parameter, which controls the walk speed by adjusting the rhythm frequency of CPG. In other words, in our model, the control of speed is primarily realized by modulating the time characteristics of walking. Compared with Güther's model, our speed control is more practical and precise.

6.4.4 Feedback delay and posture control

In the walking cycle, the feedback delay is not expected to influence the performance of human motor system. In other words, the CPG can generate the pattern a bit earlier to compensate the feedback delay, the time-shift can be predicted from the change of ground contact. However, the feedback delay is very critical to posture control [161]. The threshold control model had been proven to work as a reliable posture controller [134, 136]. Our study suggested this superiority is inherited in the proposed CPG-threshold controller: the simulation results show that minor perturbations do not impair the posture and the influence of time delay existing in the proprioceptor afferent is compensated. Compared with the previous simulation studies ignored the feedback delay [8], our study is relatively more complete as the feedback delay is included in the model.

6.5 Conclusion

In this study, we propose a FES controller for synthesizing coordinate human walking by threshold control theory and CPG. Simulation results suggest that the proposed CPG-threshold controller (depicted as equations 6.2 - 6.7) can generate rhythmical walking pattern even with significant feedback delays. The development of new controller also provide a possible explanation about the inherent mechanisms of human walking control system.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

Modeling and control of human motor system is hot topic in current research area of rehabilitation engineering. In this thesis, our work including four stages:

Firstly, we have developed a subject-specific musculoskeletal model by *in-vivo* ultrasound imaging and anthropometry. The purpose of this study is to provide a reliable platform for the implementing and testing the new control strategies.

Secondly, we have developed a series of motor controllers based on threshold control theory and its extensions. These controllers are combined with the subject-specific musculoskeletal model and tested through simulation and experiments. The purpose of this study is to find a reliable control theory that can be implemented into the FES technique. From the view of control engineering, the threshold controller is applicable to artificial human motor control because it does not need to solve the complex “reverse dynamic” problem. However, the threshold control theory is still a hypothesis and two extensions are proposed (intermittent

controller and diff. controller). Our study results validate the threshold control theory, and further suggest that modified threshold control theory (diff. controller in chapter 4) has better performance comparing with other tested controllers.

Thirdly, after validating the threshold control theory, we have applied it in the design of the FES controllers. The simulation results of upper limb movement suggest that 1) the threshold FES controller with additional angular acceleration feedback can achieve desired motion task even with large feedback delays; 2) the threshold FES controller can synthesize various feedbacks to control multi-joint movements.

Finally, we have developed an intelligent FES walking controller. The threshold control theory and another physically based control theory, CPG, are combined in our study. The results show 1) the proposed controller can achieve the desired task; 2) it is robust to feedback delays. The result also suggests the important roles of CPG and threshold control module in natural human motor control.

To sum up, the study in this thesis has proved the validation of the threshold control theory in human motor control, which is completed through experimental study and simulation study on a subject-specific musculoskeletal model. By learning from the natural control strategy, we have developed a FES controller based on the threshold control theory and proved its applicability on a paralyzed upper limb. Furthermore, we have combined two physiological based control theories: threshold control theory and CPG to achieve the complex rhythmic movement, i.e., human walking. The results show that the integrated controllers can generate the necessary muscle activation patterns for human walking with feedback delays.

7.2 Future work

This thesis has just explored a small part of human motor control. It is undoubted that there are many related topics need to be further investigated.

7.2.1 Control of the multiple degrees of freedom system

In current study, the threshold control theory and threshold FES controller are tested in the musculoskeletal system with few (1, 2 and 3) degrees of freedom (DOF). It is well-known that a real human body has more DOF than our simplified model, i.e., the human body has higher mobility than the current model. Therefore as the future work, it is planned to verify and analyze the stabilities of the threshold controller and threshold FES controller with a more complete model.

The challenges of the multiple DOF model control and analysis lie in several aspects: 1) The complexity of movement control. The improved mobility will require motor control process to perform the coordination of those multiple degrees of freedom. 2) The computation complexity of stability analysis. As shown in section 4.6, stability analysis is already quite complex for the non-linear, time-delay human motion system with 1 DOF. If the number of DOF increases, the cost of computation will be increased exponentially. 3) The interaction between different DOF. The behavior of one DOF might influence the system performance at other DOF, which should be considered and compensated in the design of the controller.

Another challenge of multiple DOF model control is the server redundancy problem, i.e., it is more difficult to choose a unique solution from more possible actions. Though we have approved that the redundancy problem can be solved with a threshold controller based on the simplified model, it may be required to conduct similar study with more complex models to verify this ability.

7.2.2 3D musculoskeletal model

To reduce the complexities of modeling and control system design, we have developed and employed the 2-D musculoskeletal models in our study. These simplified models are sufficient for validating the novel control strategy. However, since the real human limb is a 3-D system, it is required to build a 3-D model in future. For 3-D modeling, the coordinates of those muscle attachment points can be digitized using a 3-D digitizer, and the characteristics of muscles can be identified by ultrasound imaging and magnetic resonance imaging. For 3-D motion control, the threshold controller should be extended to handle higher order non-linear systems. Another approach is to divide the 3-D motion control into several 2-D motion controls.

7.2.3 Ultrasound elastography for parameters measurement

In section 3.3, a method using ultrasonography and anthropometry had been proposed to estimate the parameters of musculoskeletal model *in vivo*. The estimated parameters might not be so accurate due to the low resolution of conventional ultrasonography. To improve the accuracy, new ultrasound signal and image processing technologies can be applied.

One promising technique is ultrasound elastography. It is known that the elastography is well developed technology for measuring the soft tissue stiffness. Although magnetic resonance (MR) elastography had been used as a research tool in the study of the viscoelastic properties of skeletal muscle *in vivo* [162]. Ultrasound elastography should be more suitable for the measurement of musculoskeletal system due to the intrinsic shortcomings of MR such as tonic and high cost. Compared with conventional B-mode image, the muscular tissue can be more

clearly identified from surrounding tissue by employing ultrasound elastography, since they have different shear wave modulus. Therefore, the muscle fascicle and muscle cross-section can be more clearly observed and measured.

Publications

Journals

- [1] L. Lan, K. Y. Zhu and C. Y. Wen. “Characterization of reflex regulation of antagonist muscles based on a spinal neuro-musculoskeletal system model.” International Journal of Modeling, Identification and Control. 2010, 9(4): 382-391.

- [2] L. Lan, K. Y. Zhu and C. Y. Wen. “Design of a threshold FES control system for arm movement.” Journal of Mechanics in Medicine and Biology. 2009, 9(4): 449-479.

- [3] D. G. Zhang, X. G. Zhu, L. Lan, and K. Y. Zhu. “Mathematical Study on Ionic Mechanism of Lamprey Central Pattern Generator Model.” International Journal of Neural Systems. 2009, 19(6).

- [4] L. Lan and K. Y. Zhu. “Biomechanical stability analysis of the λ -model controlling one joint.” International Journal of Neural Systems. 2007, 17(3):193-206.

Book chapter

- [1] L. Lan, K. Y. Zhu and D. G. Zhang. “An introduction of human motor system and motor control.” in “ Distributed Diagnosis and Home Healthcare - *Volume 2* ”, American Scientific Publisher, 2010 (In Progress).
- [2] L. Lan, K. Y. Zhu. “Design of a threshold FES control system for arm movement.” in “Distributed Diagnosis and Home Healthcare - *Volume 2* ”, American Scientific Publisher, 2010 (In Progress).

Conferences

- [1] L. Lan, K. Y. Zhu and A. U. Rajendra. “FES controller design based on threshold control theory for single joint movement.” The 1st Middle East Conference on Biomedical Engineering (MECBME’11). UAE. 2011.
- [2] L. Lan, C. Y. Wen, K. Y. Zhu and L. H. Jin. “Characterization of Neuromusculoskeletal Model with Spinal Reflex Regulation” The 10th International Conference on Control, Automation, Robotics and Vision (ICARCV 2008). Vietnam. 2008.
- [3] L. Lan, C. Y. Wen, K. Y. Zhu and L. H. Jin. “Musculo-tendon parameters estimation by ultrasonography for modeling of human motor system.” The 13th International Conference on Biomedical Engineering (ICBME2008). Singapore. 2008.

- [4] L. Lan and K. Y. Zhu. “Stability Analysis of the λ -model During Fast Elbow Movements.” The 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. (EMBC’07), France. 2007.
- [5] L. Lan, K. Y. Zhu and D. Zhao. “Stabilizing function of the λ -model with the tiny moment of inertia in a single joint limb system.” 2007 IEEE International Conference on Control and Automation (ICCA 2007). China. 2007.
- [6] L. Lan and K. Y. Zhu. “Design and implementation of blood pressure regulation systems.” The international Convention for Rehabilitation Engineering & Assistive Technology (i-CREATE 2007).
- [7] L. Lan and K. Y. Zhu. “Destabilizing Effects of Time-Delay in Lambda-Model for Human Postural Control.” The international Convention for Rehabilitation Engineering & Assistive Technology (i-CREATE 2007).
- [8] L. Lan, K. Y. Zhu and D. G. Zhang. “Modeling and Control of Human Motor System with Generalized Predictive Control.” 2006 IEEE International Conference on Cybernetics and Intelligent Systems and IEEE International Conference on Robotics, Automation and Mechatronics (CIS-RAM 2006). Thailand. 2006.
- [9] L. Lan and K. Y. Zhu. “Stability Analysis of λ -model for Human Motor System”. The 9th International Conference on Control, Automation, Robotics and Vision (ICARCV 2006). Singapore. 2006.

- [10] K. Y. Zhu, D. G. Zhang and L. Lan. “On Central Pattern Generator of Biological Motor System”. The 9th International Conference on Control, Automation, Robotics and Vision (ICARCV 2006). Singapore. 2006.

- [11] L. Lan, K. Y. Zhu and Y. L. Wu “Modeling and Analysis of Human Spinal Feedback Control System”. The International Conference on Biomedical and Pharmaceutical Engineering 2006 (ICBPE 2006). Singapore. 2006. (Outstanding Paper Award)

- [12] Y. L. Wu, Q. Song, X. L. Yang and L. Lan. “Recurrent Neural Network Control of Functional Electrical Stimulation Systems”. The International Conference on Biomedical and Pharmaceutical Engineering 2006 (ICBPE 2006). Singapore. 2006.

Bibliography

- [1] T. A. McMahon, *Muscles, Reflexes, and Locomotion*, Princeton University Press, 1984.
- [2] N. Lan, Y. Li, Y. Sun, and F. S. Yang, “Reflex regulation of antagonist muscles for control of joint equilibrium position,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, no. 1, pp. 60–71, 2005.
- [3] J. P. He, M. G. Maltenfort, Q. J. Wang, and T. M. Hamm, “Learning from biological systems: modeling neural control,” *IEEE Control Systems Magazine*, vol. 21, no. 4, pp. 55–69, 2001.
- [4] H. E. J. Veeger, B. Yu, K. N. An, and R. H. Rozendal, “Parameters for modeling the upper extremity,” *Journal of Biomechanics*, vol. 30, no. 6, pp. 647–652, 1997.
- [5] W. M. Murray, T. S. Buchanan, and S. L. Delp, “The isometric functional capacity of muscles that cross the elbow,” *Journal of Biomechanics*, vol. 33, no. 8, pp. 943–952, 2000.

- [6] K. N. An, K. Takahashi, T. P. Harrigan, and E. Y. Chao, “Determination of muscle orientations and moment arms,” *J Biomech Eng*, vol. 106, no. 3, pp. 280–2, 1984.
- [7] H. E. J. Veeger, F. C. T. Van Der Helm, L. H. V. Van Der Woude, G. M. Pronk, and R. H. Rozendal, “Inertia and muscle contraction parameters for musculoskeletal modelling of the shoulder mechanism,” *Journal of Biomechanics*, vol. 24, no. 7, pp. 615–629, 1991.
- [8] M. Günther and H. Ruder, “Synthesis of two-dimensional human walking: a test of the lambda-model,” *Biol Cybern*, vol. 89, no. 2, pp. 89–106, 2003.
- [9] T. G. Brown, “The intrinsic factors in the act of progression in the mammal,” *Proceedings of the Royal Society of London. Series B, Containing Papers of a Biological Character (1905-1934)*, vol. 84, no. 572, pp. 308–319, 1911.
- [10] G. N. Orlovsky, T. G. Deliagina, and S. Grillner, *Neural Control of Locomotion. From Mollusk to Man*, Oxford University Press, 1999.
- [11] D. A. Kistemaker, A. J. Van Soest, and M. F. Bobbert, “Is equilibrium point control feasible for fast goal-directed single-joint movements?,” *J Neurophysiol*, vol. 95, no. 5, pp. 2898–912, 2006.
- [12] J. McIntyre and E. Bizzi, “Servo hypotheses for the biological control of movement,” *J Mot Behav*, vol. 25, no. 3, pp. 193–202, 1993.
- [13] J. H. J. Allum, B. R. Bloem, M. G. Carpenter, M. Hulliger, and M. Hadders-Algra, “Proprioceptive control of posture: a review of new concepts,” *Gait and Posture*, vol. 8, no. 3, pp. 214–242, 1998.

- [14] K. Doya, H. Kimura, and M. Kawato, “Neural mechanisms of learning and control,” *IEEE Control Systems Magazine*, vol. 21, no. 4, pp. 42–54, 2001.
- [15] D. A. Rosenbaum, *Human motor control*, Academic Press San Diego, CA, 1990.
- [16] J. F. Stein and M. Glickstein, “Role of the cerebellum in visual guidance of movement,” 1992.
- [17] R. Davoodi and G. E. Loeb, “A biomimetic strategy for control of fcs reaching,” in *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, G. E. Loeb, Ed., 2003, vol. 2, pp. 1746–1749 Vol.2.
- [18] A. W. David, *Biomechanics and Motor Control of Human Movement*, John Wiley and Sons Inc, 2004.
- [19] P. J. Whelan, “Developmental aspects of spinal locomotor function: insights from using the in vitro mouse spinal cord preparation,” 2003.
- [20] O. Kiehn and S. J. B. Butt, “Physiological, anatomical and genetic identification of cpg neurons in the developing mammalian spinal cord,” *Progress in Neurobiology*, vol. 70, no. 4, pp. 347–361, 2003.
- [21] I. A. Rybak, K. Stecina, N. A. Shevtsova, and D. A. McCrea, “Modelling spinal circuitry involved in locomotor pattern generation: insights from the effects of afferent stimulation,” *The Journal of Physiology*, vol. 577, no. 2, pp. 641, 2006.
- [22] G. E. Loeb, I. E. Brown, and E. J. Cheng, “A hierarchical foundation for models of sensorimotor control,” *Experimental Brain Research*, vol. 126, no. 1, pp. 1–18, 1999.

- [23] F. E. Zajac, “Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control,” *Crit Rev Biomed Eng*, vol. 17, no. 4, pp. 359–411, 1989.
- [24] A. Freivalds, *Biomechanics of the upper limbs: mechanics, modeling, and musculoskeletal injuries*, CRC, 2004.
- [25] I. E. Brown and G. E. Loeb, “Measured and modeled properties of mammalian skeletal muscle: Iv. dynamics of activation and deactivation,” *J Muscle Res Cell Motil*, vol. 21, no. 1, pp. 33–47, 2000.
- [26] M. L. Latash and M. F. Levin, *Progress in Motor Control: Effects of Age, Disorder, and Rehabilitation*, Champaign, IL: Human Kinetics, 2003.
- [27] N. A. Dimitrova, T. I. Arabadzhiev, J. Y. Hogrel, and G. V. Dimitrov, “Fatigue analysis of interference emg signals obtained from biceps brachii during isometric voluntary contraction at various force levels,” *Journal of Electromyography and Kinesiology*, vol. 19, no. 2, pp. 252–258, 2009.
- [28] A. V. Hill, *First and last experiments in muscle mechanics*, Cambridge UP, 1970.
- [29] I. E. Brown, E. J. Cheng, and G. E. Loeb, “Measured and modeled properties of mammalian skeletal muscle. ii. the effects of stimulus frequency on force-length and force-velocity relationships,” *J Muscle Res Cell Motil*, vol. 20, no. 7, pp. 627–43, 1999.
- [30] P. B. C. Matthews, *Mammalian muscle receptors and their central actions*, Hodder Arnold, 1972.

- [31] W. M. Kistler, W. Gerstner, and J. L. Hemmen, “Reduction of the hodgkin-huxley equations to a single-variable threshold model,” *Neural Computation*, vol. 9, no. 5, pp. 1015–1045, 1997.
- [32] G. L. Gottlieb and G. C. Agarwal, “Effects of initial conditions on the hoffman reflex,” *J Neurol Neurosurg Psychiatry*, vol. 34, no. 3, pp. 226–30, 1971.
- [33] A. F. Huxley, “Muscle structure and theories of contraction,” *Prog Biophys Biophys Chem*, vol. 7, pp. 255–318, 1957.
- [34] T. L. Hill, *Free energy transduction in biology*, Academic Press New York, 1977.
- [35] A.V. Hill, “The heat of shortening and the dynamic constants of muscle,” *Proceedings of the Royal Society of London. Series B, Biological Sciences*, vol. 126, no. 843, pp. 136–195, 1938.
- [36] H. Gollee, D. J. Murray-Smith, and J. C. Jarvis, “A nonlinear approach to modeling of electrically stimulated skeletal muscle,” *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 4, pp. 406–415, 2001.
- [37] S. J. Dorgan and M. J. O’Malley, “A nonlinear mathematical model of electrically stimulated skeletal muscle,” *IEEE Transactions on Rehabilitation Engineering [see also IEEE Trans. on Neural Systems and Rehabilitation Engineering]*, vol. 5, no. 2, pp. 179–194, 1997.
- [38] P. P. Van Der Smagt and B. J. A. Krose, “A real-time learning neural robot controller,” 1991, vol. 1, pp. 351–356, Citeseer.

- [39] M. V. Butz, O. Herbort, and J. Hoffmann, “Exploiting redundancy for flexible behavior: Unsupervised learning in a modular sensorimotor control architecture,” *Psychological Review*, vol. 114, no. 4, pp. 1015–1046, 2007.
- [40] E. Otten, “Inverse and forward dynamics: models of multibody systems,” *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, vol. 358, no. 1437, pp. 1493–1500, 2003.
- [41] S. R. Goodman and M. L. Latash, “Feed-forward control of a redundant motor system,” *Biol Cybern*, 2006.
- [42] A. V. Alexandrov, A. A. Frolov, F. B. Horak, P. Carlson-Kuhta, and S. Park, “Feedback equilibrium control during human standing,” *Biol Cybern*, vol. 93, no. 5, pp. 309–22, 2005.
- [43] A. G. Feldman and M. F. Levin, “The origin and use of positional frames of reference in motor control,” *Behavioral and Brain Sciences*, vol. 18, no. 4, pp. 723–806, 1995.
- [44] N. St-Onge, S. V. Adamovich, and A. G. Feldman, “Control processes underlying elbow flexion movements may be independent of kinematic and electromyographic patterns: experimental study and modelling,” *Neuroscience*, vol. 79, no. 1, pp. 295–316, 1997.
- [45] P. L. Gribble, D. J. Ostry, V. Sanguineti, and R. Laboissiere, “Are complex control signals required for human arm movement?,” *J Neurophysiol*, vol. 79, no. 3, pp. 1409–24, 1998.
- [46] J. F. Pilon and A. G. Feldman, “Threshold control of motor actions prevents destabilizing effects of proprioceptive delays,” *Exp Brain Res*, vol. 174, no. 2, pp. 229–39, 2006.

- [47] M. R. Hinder and T. E. Milner, “The case for an internal dynamics model versus equilibrium point control in human movement,” *J Physiol*, vol. 549, no. Pt 3, pp. 953–63, 2003.
- [48] A. G. Feldman and M. L. Latash, “Testing hypotheses and the advancement of science: recent attempts to falsify the equilibrium point hypothesis,” *Exp Brain Res*, vol. 161, no. 1, pp. 91–103, 2005.
- [49] N. Hogan, “An organizing principle for a class of voluntary movements,” *J Neurosci*, vol. 4, no. 11, pp. 2745–54, 1984.
- [50] M. L. Latash and G. L. Gottlieb, “Reconstruction of shifting elbow joint compliant characteristics during fast and slow movements,” *Neuroscience*, vol. 43, no. 2-3, pp. 697–712, 1991.
- [51] N. Schweighofer, M. A. Arbib, and M. Kawato, “Role of the cerebellum in reaching movements in humans. i. distributed inverse dynamics control,” *Eur J Neurosci*, vol. 10, no. 1, pp. 86–94, 1998.
- [52] G. L. Gottlieb, “Rejecting the equilibrium-point hypothesis,” *Motor Control*, vol. 2, no. 1, pp. 10–2, 1998.
- [53] F. Popescu, J. M. Hidler, and W. Z. Rymer, “Elbow impedance during goal-directed movements,” *Exp Brain Res*, vol. 152, no. 1, pp. 17–28, 2003.
- [54] N. St-Onge, H. Qi, and A. G. Feldman, “The patterns of control signals underlying elbow joint movements in humans,” *Neurosci Lett*, vol. 164, no. 1-2, pp. 171–4, 1993.
- [55] A. G. Feldman, “Once more on the equilibrium-point hypothesis (lambda model) for motor control,” *J Mot Behav*, vol. 18, no. 1, pp. 17–54, 1986.

- [56] A. G. Feldman, S. V. Adamovich, and M. F. Levin, “The relationship between control, kinematic and electromyographic variables in fast single-joint movements in humans,” *Exp Brain Res*, vol. 103, no. 3, pp. 440–50, 1995.
- [57] J. H. Moe and H. W. Post, “Functional electrical stimulation for ambulation in hemiplegia,” *J Lancet*, vol. 82, pp. 285–8, 1962.
- [58] P. E. Crago, P. H. Peckham, and G. B. Thrope, “Modulation of muscle force by recruitment during intramuscular stimulation,” *IEEE Transactions on Biomedical Engineering*, pp. 679–684, 1980.
- [59] S. A. Binder-Macleod, S. C. Lee, D. W. Russ, and L. J. Kucharski, “Effects of activation pattern on human skeletal muscle fatigue,” *Muscle Nerve*, vol. 21, no. 9, pp. 1145–52, 1998.
- [60] J. R. Buckett, P. H. Peckham, G. B. Thrope, S. D. Braswell, and M. W. Keith, “A flexible, portable system for neuromuscular stimulation in the paralyzed upper extremity,” *IEEE Transactions on Biomedical Engineering*, vol. 35, no. 11, pp. 897–904, 1988.
- [61] N. Hoshimiya, A. Naito, M. Yajima, and Y. Handa, “A multichannel fes system for the restoration of motor functions in high spinal cord injury patients: a respiration-controlled system for multi-joint upper extremity,” *IEEE Transactions on Biomedical Engineering*, vol. 36, no. 7, pp. 754–760, 1989.
- [62] P. E. Crago, J. T. Mortimer, and P. H. Peckham, “Closed-loop control of force during electrical stimulation of muscle,” *IEEE Transactions on Biomedical Engineering*, pp. 306–312, 1980.

- [63] H. J. Chizeck, N. Lan, L. S. Palmieri, and P. E. Crago, “Feedback control of electrically stimulated muscle using simultaneous pulse width and stimulus period modulation,” *IEEE Transactions on Biomedical Engineering*, vol. 38, no. 12, pp. 1224–34, 1991.
- [64] M. A. Lemay, P. E. Crago, R. E. Center, M. H. M. Center, and O. H. Cleveland, “Closed-loop wrist stabilization in c4 and c5 tetraplegia,” *IEEE Transactions on Rehabilitation Engineering [see also IEEE Trans. on Neural Systems and Rehabilitation Engineering]*, vol. 5, no. 3, pp. 244–252, 1997.
- [65] M. S. Hatwell, B. J. Oderkerk, C. A. Sacher, and G. F. Inbar, “The development of a model reference adaptive controller to control the knee joint of paraplegics,” *IEEE Transactions on Automatic Control*, vol. 36, no. 6, pp. 683–691, 1991.
- [66] F. Towhidkhah, R. E. Gander, and H. C. Wood, “Model predictive impedance control: A model for joint movement,” *J Mot Behav*, vol. 29, no. 3, pp. 209–222, 1997.
- [67] L. A. Bernotas, P. E. Crago, and H. J. Chizeck, “Adaptive control of electrically stimulated muscle,” *IEEE Transactions on Biomedical Engineering*, pp. 140–147, 1987.
- [68] R. Davoodi and B. J. Andrews, “Computer simulation of fes standing up in paraplegia: a self-adaptive fuzzy controller with reinforcement learning,” *IEEE Transactions on Rehabilitation Engineering [see also IEEE Trans. on Neural Systems and Rehabilitation Engineering]*, vol. 6, no. 2, pp. 151–161, 1998.

- [69] H. Qi, D. J. Tyler, and D. M. Durand, “Neurofuzzy adaptive controlling of selective stimulation for fes: a case study,” *IEEE Transactions on Rehabilitation Engineering* [see also *IEEE Trans. on Neural Systems and Rehabilitation Engineering*], vol. 7, no. 2, pp. 183–192, 1999.
- [70] P. R. Davidson, R. D. Jones, J. H. Andreae, and H. R. Sirisena, “Simulating closed-and open-loop voluntary movement: a nonlinear control-systems approach,” *IEEE Transactions on Biomedical Engineering*, vol. 49, no. 11, pp. 1242–1252, 2002.
- [71] R. Davoodi and B. J. Andrews, “Fuzzy logic control of fes rowing exercise in paraplegia,” *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 3, pp. 541–543, 2004.
- [72] S. Micera, A. M. Sabatini, and P. Dario, “Adaptive fuzzy control of electrically stimulated muscles for arm movements,” *Medical and Biological Engineering and Computing*, vol. 37, no. 1, pp. 680–685, 1999.
- [73] H. Dou, K. K. Tan, T. H. Lee, and Z. Zhou, “Iterative learning feedback control of human limbs via functional electrical stimulation,” *Control Engineering Practice*, vol. 7, no. 3, pp. 315–325, 1999.
- [74] K. J. Hunt, R. P. Jaime, and H. Gollee, “Robust control of electrically-stimulated muscle using polynomial h-infinity design,” *Control Engineering Practice*, vol. 9, no. 3, pp. 313–328, 2001.
- [75] S. Jezernik, P. Inderbitzin, T. Keller, and R. Riener, “A novel sliding mode controller for functional electrical stimulation,” *Proceedings of the 15th IFAC World Congress on Automatic Control, Barcelona Session slot T-Mo-M20: Modelling and Control in Biomedical Systems*, vol. 5, 2002.

- [76] S. Jezernik, B. Ag, and S. Basel, “Design of multiple degree-of-freedom sliding mode fcs controller for concurrent stimulation of multiple mono and biarticulate muscles,” *Engineering in Medicine and Biology Society, 2004. EMBC 2004. Conference Proceedings. 26th Annual International Conference of the*, vol. 2, 2004.
- [77] F. Previdi, T. Schauer, S. M. Savaresi, and K. J. Hunt, “Data-driven control design for neuroprostheses: a virtual reference feedback tuning (vrft) approach,” *IEEE Transactions on Control Systems Technology*, vol. 12, no. 1, pp. 176–182, 2004.
- [78] N. Lan, H. Q. Feng, and E. Crago, “Neural network generation of muscle stimulation patterns for control of arm movements,” *IEEE Transactions on Rehabilitation Engineering*, vol. 2, no. 4, pp. 213, 1994.
- [79] J. J. Abbas and H. J. Chizeck, “Neural network control of functional neuromuscular stimulationsystems: computer simulation studies,” *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 11, pp. 1117–1127, 1995.
- [80] G. C. Chang, J. J. Luh, J. S. L. Gon-Der Liao, C. K. Cheng, B. L. Kuo, and T. S. Kuo, “A neuro-control system for the knee joint position control with quadriceps stimulation,” *IEEE Transactions on Rehabilitation Engineering*, vol. 5, no. 1, pp. 2–11, 1997.
- [81] K. Tong and M. Granat, “Gait control system for functional electrical stimulation using neural networks,” *Medical and Biological Engineering and Computing*, vol. 37, no. 1, pp. 35–41, 1999.
- [82] M. Rakos, B. Freudenschu, W. Girsch, C. Hofer, J. Kaus, T. Meiners, T. Patermostro, and W. Mayr, “Electromyogram-controlled functional electrical

- stimulation for treatment of the paralyzed upper extremity,” *Artif Organs*, vol. 23, no. 5, pp. 466–469, 1999.
- [83] J. Riess and J. J. Abbas, “Adaptive neural network control of cyclic movements using functional neuromuscular stimulation,” *IEEE Transactions on Rehabilitation Engineering [see also IEEE Trans. on Neural Systems and Rehabilitation Engineering]*, vol. 8, no. 1, pp. 42–52, 2000.
- [84] R. Davoodi, M. Hauschild, J. Lee, P. T. Montazemi, and G. E. Loeb, “Biomimetic control of fes reaching,” 2005, pp. 177–181.
- [85] K. Kurosawa, R. Futami, T. Watanabe, and N. Hoshimiya, “Joint angle control by fes using a feedback error learning controller,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, no. 3, pp. 359–371, 2005.
- [86] D.G. Zhang and K.Y. Zhu, “Modeling biological motor control for human locomotion with functional electrical stimulation,” *Biol Cybern*, vol. 96, no. 1, pp. 79–97, 2007.
- [87] M. G. Pandy, “Computer modeling and simulation of human movement,” *Annual Review of Biomedical Engineering*, vol. 3, no. 1, pp. 245–273, 2001.
- [88] M. A. Lemay and P. E. Crago, “A dynamic model for simulating movements of the elbow, forearm, and wrist,” *Journal of Biomechanics*, vol. 29, no. 10, pp. 1319–1330, 1996.
- [89] R. V. Gonzalez, T. S. Buchanan, and S. L. Delp, “How muscle architecture and moment arms affect wrist flexion-extension moments,” *Journal of Biomechanics*, vol. 30, no. 7, pp. 705–712, 1997.

- [90] N. Lan, “Stability analysis for postural control in a two-joint limb system,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 10, no. 4, pp. 249–59, 2002.
- [91] D. C. Martin, M. K. Medri, R. S. Chow, V. Oxorn, R. N. Leekam, A. M. Agur, and N. H. McKee, “Comparing human skeletal muscle architectural parameters of cadavers with in vivo ultrasonographic measurements,” *J Anat*, vol. 199, no. Pt 4, pp. 429–34, 2001.
- [92] P. W. Brand, R. B. Beach, and D. E. Thompson, “Relative tension and potential excursion of muscles in the forearm and hand,” *J Hand Surg [Am]*, vol. 6, no. 3, pp. 209–19, 1981.
- [93] K. Sanada, C. Kearns, T. Midorikawa, and T. Abe, “Prediction and validation of total and regional skeletal muscle mass by ultrasound in japanese adults,” *European Journal of Applied Physiology*, vol. 96, no. 1, pp. 24–31, 2006.
- [94] R. C. Lee, Z. Wang, M. Heo, R. Ross, I. Janssen, and S. B. Heymsfield, “Total-body skeletal muscle mass: development and cross-validation of anthropometric prediction models,” *Am J Clin Nutr*, vol. 72, no. 3, pp. 796–803, 2000.
- [95] C. N. Maganaris, V. Baltzopoulos, and A. J. Sargeant, “Changes in the tibialis anterior tendon moment arm from rest to maximum isometric dorsiflexion: in vivo observations in man,” *Clin Biomech (Bristol, Avon)*, vol. 14, no. 9, pp. 661–6, 1999.
- [96] L. Li and K. Y. Tong, “Musculotendon parameters estimation by ultrasound measurement and geometric modeling: application on brachialis muscle,” in

- Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2005, pp. 4974–4977.
- [97] K. Luttgens and N. Hamilton, *Kinesiology: Scientific Basis of Human Motion*, Brown and Benchmark. 9th edition, 1997.
- [98] J. E. Desmedt, “Size principle of motoneuron recruitment and the calibration of muscle force and speed in man,” *Adv Neurol*, vol. 39, pp. 227–51, 1983.
- [99] I. E. Brown, S. H. Scott, and G. E. Loeb, “Mechanics of feline soleus: Ii design and validation of a mathematical model,” *Journal of Muscle Research and Cell Motility*, vol. 17, no. 2, pp. 221–233, 1996.
- [100] E. J. Cheng, I. E. Brown, and G. E. Loeb, “Virtual muscle: a computational approach to understanding the effects of muscle properties on motor control,” *J Neurosci Methods*, vol. 101, no. 2, pp. 117–30, 2000.
- [101] A. J. van Soest and M. F. Bobbert, “The contribution of muscle properties in the control of explosive movements,” *Biol Cybern*, vol. 69, no. 3, pp. 195–204, 1993.
- [102] C. S. Cook and M. J. N. McDonagh, “Measurement of muscle and tendon stiffness in man,” *European Journal of Applied Physiology*, vol. 72, no. 4, pp. 380–382, 1996.
- [103] C. N. Maganaris and M. V. Narici, “Mechanical properties of tendons,” in *Tendon Injuries*, pp. 14–21. 2005.
- [104] J. C. Tabary, C. Tardieu, G. Tardieu, C. Tabary, and L. Gagnard, “Functional adaptation of sarcomere number of normal cat muscle,” *J Physiol (Paris)*, vol. 72, no. 3, pp. 277–91, 1976.

- [105] J. Langenderfer, S. A. Jerabek, V. B. Thangamani, J. E. Kuhn, and R. E. Hughes, “Musculoskeletal parameters of muscles crossing the shoulder and elbow and the effect of sarcomere length sample size on estimation of optimal muscle length,” *Clinical Biomechanics*, vol. 19, no. 7, pp. 664–670, 2004.
- [106] Y. Kawakami, K. Nakazawa, T. Fujimoto, D. Nozaki, M. Miyashita, and T. Fukunaga, “Specific tension of elbow flexor and extensor muscles based on magnetic resonance imaging,” *European Journal of Applied Physiology*, vol. 68, no. 2, pp. 139–147, 1994.
- [107] S. C. Cannon and G. I. Zahalak, “The mechanical behavior of active human skeletal muscle in small oscillations,” *J Biomech*, vol. 15, no. 2, pp. 111–21, 1982.
- [108] T. Flash and F. Mussa-Ivaldi, “Human arm stiffness characteristics during the maintenance of posture,” *Exp Brain Res*, vol. 82, no. 2, pp. 315–26, 1990.
- [109] D. G. Thelen, “Adjustment of muscle mechanics model parameters to simulate dynamic contractions in older adults,” *J Biomech Eng*, vol. 125, no. 1, pp. 70–7, 2003.
- [110] M. Ikai and T. Fukunaga, “Calculation of muscle strength per unit cross-sectional area of human muscle by means of ultrasonic measurement,” *European Journal of Applied Physiology*, vol. 26, no. 1, pp. 26–32, 1968.
- [111] R. Chhem and E. Cardinal, *Guidelines and Gamuts in Musculoskeletal Ultrasound*, Wiley-Liss, 1999.
- [112] M. Backhaus, G. R. Burmester, T. Gerber, W. Grassi, K. P. Machold, W. A. Swen, R. J. Wakefield, and B. Manger, “Guidelines for musculoskeletal ul-

- trasound in rheumatology,” *Annals of the Rheumatic Diseases*, vol. 60, no. 7, pp. 641–649, 2001.
- [113] K. Finlay, M. Ferri, and L. Friedman, “Ultrasound of the elbow,” *Skeletal Radiology*, vol. 33, no. 2, pp. 63–79, 2004.
- [114] S. A. Spector, P. F. Gardiner, R. F. Zernicke, R. R. Roy, and V. R. Edgerton, “Muscle architecture and force-velocity characteristics of cat soleus and medial gastrocnemius: implications for motor control,” *J Neurophysiol*, vol. 44, no. 5, pp. 951–60, 1980.
- [115] B. A. Garner and M. G. Pandy, “Estimation of musculotendon properties in the human upper limb,” *Annals of Biomedical Engineering*, vol. 31, no. 2, pp. 207–220, 2003.
- [116] W. A. Weijss and B. Hillen, “Cross-sectional areas and estimated intrinsic strength of the human jaw muscles,” *Acta Morphol Neerl Scand*, vol. 23, no. 3, pp. 267–74, 1985.
- [117] C. K. Thomas, R. S. Johansson, and B. Bigland-Ritchie, “Pattern of pulses that maximize force output from single human thenar motor units,” *J Neurophysiol*, vol. 82, no. 6, pp. 3188–95, 1999.
- [118] L. G. Paul and J. O. David, “Compensation for loads during arm movements using equilibrium-point control,” *Experimental Brain Research*, vol. 135, no. 4, pp. 474–482, 2000.
- [119] J. F. Pilon, S. De Serres, and A.G. Feldman, “Threshold position control of arm movement with anticipatory increase in grip force,” *Experimental Brain Research*, vol. 181, no. 1, pp. 49–67, 2007.

- [120] A. G. Feldman, V. Goussev, A. Sangole, M. F. Levin, Trevor D. Paul C., and John F. K., “Threshold position control and the principle of minimal interaction in motor actions,” in *Progress in Brain Research*, vol. Volume 165, pp. 267–281. Elsevier, 2007.
- [121] A. G. Feldman, “Threshold position control signifies a common spatial frame of reference for motor action and kinesthesia,” *Brain Research Bulletin*, vol. 75, no. 5, pp. 497–499, 2008.
- [122] N. St-Onge, N. Duval, L. Yahia, and A. G. Feldman, “Interjoint coordination in lower limbs in patients with a rupture of the anterior cruciate ligament of the knee joint,” *Knee Surg Sports Traumatol Arthrosc*, vol. 12, no. 3, pp. 203–16, 2004.
- [123] F. Lestienne, “Effects of inertial load and velocity on the braking process of voluntary limb movements,” *Exp Brain Res*, vol. 35, no. 3, pp. 407–18, 1979.
- [124] N. Hogan, “Adaptive control of mechanical impedance by coactivation of antagonist muscles,” *IEEE Transactions on Automatic Control*, vol. 29, no. 8, pp. 681–690, 1984.
- [125] B. A. Conway, P. Biswas, D. M. Halliday, S. F. Farmer, and J. R. Rosenberg, “Task-dependent changes in rhythmic motor output during voluntary elbow movement in man,” *The Journal of Physiology*, vol. 501, pp. 48–49, 1997.
- [126] J. A. Doeringer and N. Hogan, “Intermittency in preplanned elbow movements persists in the absence of visual feedback,” *Journal of Neurophysiology*, vol. 80, no. 4, pp. 1787–1799, 1998.

- [127] J. Gross, L. Timmermann, J. Kujala, M. Dirks, F. Schmitz, R. Salmelin, and A. Schnitzler, “The neural basis of intermittent motor control in humans,” *Proceedings of the National Academy of Sciences*, vol. 99, no. 4, pp. 2299, 2002.
- [128] B. Pollok, J. Gross, K. Muller, G. Aschersleben, and A. Schnitzler, “The cerebral oscillatory network associated with auditorily paced finger movements,” *NeuroImage*, vol. 24, no. 3, pp. 646–655, 2005.
- [129] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, “Development of recommendations for semg sensors and sensor placement procedures,” *J Electromyogr Kinesiol*, vol. 10, no. 5, pp. 361–74, 2000.
- [130] M. B. Raez, M. S. Hussain, and F. Mohd-Yasin, “Techniques of emg signal analysis: detection, processing, classification and applications,” *Biol Proced Online*, vol. 8, pp. 11–35, 2006.
- [131] L. A. Kallenberg and H. J. Hermens, “Behaviour of a surface emg based measure for motor control: Motor unit action potential rate in relation to force and muscle fatigue,” *J Electromyogr Kinesiol*, 2007.
- [132] A. Jacks, A. Prochazka, and P. S. Trend, “Instability in human forearm movements studied with feed-back-controlled electrical stimulation of muscles,” *J Physiol*, vol. 402, pp. 443–61, 1988.
- [133] K. Funase and T. S. Miles, “Observations on the variability of the h reflex in human soleus,” *Muscle Nerve*, vol. 22, no. 3, pp. 341–6, 1999.
- [134] P. Micheau, A. Kron, and P. Bourassa, “Evaluation of the lambda model for human postural control during ankle strategy,” *Biol Cybern*, vol. 89, no. 3, pp. 227–36, 2003.

- [135] L. Lan and K. Y. Zhu, “Biomechanical stability analysis of the lambda-model controlling one joint,” *Int J Neural Syst*, vol. 17, no. 3, pp. 193–206, 2007.
- [136] L. Lan and K. Y. Zhu, “Destabilizing effects of time-delay in lambda-model for human postural control,” *Proceedings of the 1st international convention on Rehabilitation engineering and assistive technology: in conjunction with 1st Tan Tock Seng Hospital Neurorehabilitation Meeting*, pp. 92–97, 2007.
- [137] A. L. Hof, “The force resulting from the action of mono-and biarticular muscles in a limb,” *Journal of Biomechanics*, vol. 34, no. 8, pp. 1085–1089, 2001.
- [138] H. Wagner and R. Blickhan, “Stabilizing function of skeletal muscles: an analytical investigation,” *J Theor Biol*, vol. 199, no. 2, pp. 163–79, 1999.
- [139] J. J. E. Slotine and W.P. Li, *Applied Nonlinear Control*, Prentice-Hall International, Inc., 1991.
- [140] W. Lohmiller and J. J. E. Slotine, “On contraction analysis for non-linear systems,” *Automatica*, vol. 34, pp. 683–696, 1998.
- [141] H. Gomi and M. Kawato, “Human arm stiffness and equilibrium-point trajectory during multi-joint movement,” *Biol Cybern*, vol. 76, no. 3, pp. 163–71, 1997.
- [142] K. Domen, L. Meigen, J. Shindo, N. Yoshida, S. Sonoda, Y. Sugimoto, and N. Chino, “A new control system for functional electrical stimulation (fes) using the lambda-model: a preliminary study on single-joint movement,” *Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control*, vol. 97, no. 4, pp. 213–213, 1995.

- [143] M. Ferrarin, F. Palazzo, R. Riener, and J. Quintern, “Model-based control of fes-induced single joint movements,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 9, no. 3, pp. 245–57, 2001.
- [144] R. Riener, J. Quintern, and G. Schmidt, “Biomechanical model of the human knee evaluated by neuromuscular stimulation,” *J Biomech*, vol. 29, no. 9, pp. 1157–67, 1996.
- [145] R. Riener and T. Fuhr, “Patient-driven control of fes-supported standing up: a simulation study,” *IEEE Transactions on Rehabilitation Engineering*, vol. 6, no. 2, pp. 113–24, 1998.
- [146] R. Riener, M. Ferrarin, E. E. Pavan, and C. A. Frigo, “Patient-driven control of fes-supported standing up and sitting down: experimental results,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 4, pp. 523–9, 2000.
- [147] A. R. Kralj and T. Bajd, *Functional electrical stimulation : standing and walking after spinal cord injury*, CRC Press, Boca Raton, Fla., 1989, Alojz R. Kralj, Tadej Bajd.
- [148] J. Ding, A. S. Wexler, and S. A. Binder-Macleod, “A predictive fatigue model-i: Predicting the effect of stimulation frequency and pattern on fatigue,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 10, no. 1, pp. 48–58, 2002.
- [149] J. Ding, A. S. Wexler, and S. A. Binder-Macleod, “A predictive fatigue model-ii: Predicting the effect of resting times on fatigue,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 10, no. 1, pp. 59–67, 2002.

- [150] A. Prochazka, “Comparison of natural and artificial control of movement,” *IEEE Transactions on Rehabilitation Engineering [see also IEEE Trans. on Neural Systems and Rehabilitation Engineering]*, vol. 1, no. 1, pp. 7–17, 1993.
- [151] M. P. Mileusnic, I. E. Brown, N. Lan, and G. E. Loeb, “Mathematical models of proprioceptors. i. control and transduction in the muscle spindle,” *J Neurophysiol*, vol. 96, no. 4, pp. 1772–88, 2006.
- [152] E. J. van Zuylen, A. van Velzen, and J. J. Denier van der Gon, “A biomechanical model for flexion torques of human arm muscles as a function of elbow angle,” *J Biomech*, vol. 21, no. 3, pp. 183–90, 1988.
- [153] P. Cesari, T. Shiratori, P. Olivato, and M. Duarte, “Analysis of kinematically redundant reaching movements using the equilibrium-point hypothesis,” *Biol Cybern*, vol. 84, no. 3, pp. 217–26, 2001.
- [154] D. G. Zhang, *Model and Neural Control of Human Lower Limb Movements with Functional Electrical Stimulation*, Ph.D. thesis, Nanyang Technological University, 2007.
- [155] D. G. Zhang, K.Y. Zhu, and H. Zheng, “Model the leg cycling movement with neural oscillator,” in *2004 IEEE International Conference on Systems, Man and Cybernetics*, 2004, vol. 1.
- [156] F. E. Zajac, R. R. Neptune, and S. A. Kautz, “Biomechanics and muscle coordination of human walking: Part ii: Lessons from dynamical simulations and clinical implications,” *Gait and Posture*, vol. 17, no. 1, pp. 1–17, 2003.
- [157] G. Taga, “A model of the neuro-musculo-skeletal system for human locomotion. i. emergence of basic gait,” *Biol Cybern*, vol. 73, no. 2, pp. 97–111, 1995.

- [158] G. Taga, “A model of the neuro-musculo-skeletal system for human locomotion. ii real-time adaptability under various constraints,” *Biol Cybern*, vol. 73, no. 2, pp. 113–21, 1995.
- [159] A. M. Arsenio, “On stability and error bounds of describing functions for oscillatory control of movements,” 2000, vol. 2.
- [160] M. F. Levin, R. W. Selles, M. H. G. Verheul, and O. G. Meijer, “Deficits in the coordination of agonist and antagonist muscles in stroke patients: implications for normal motor control,” *Brain Research*, vol. 853, no. 2, pp. 352–369, 2000.
- [161] R. J. Peterka and M. S. Benolken, “Role of somatosensory and vestibular cues in attenuating visually induced human postural sway,” *Experimental Brain Research*, vol. 105, no. 1, pp. 101–110, 1995.
- [162] M. A. Dresner, H. R. Gregory, J. R. Phillip, M. Raja, M. Armando, and L. E. Richard, “Magnetic resonance elastography of skeletal muscle,” *Journal of Magnetic Resonance Imaging*, vol. 13, no. 2, pp. 269–276, 2001.

Appendix

Selected experiment photos of ultrasound measurement

anthropometry

Figure A.1: Experiment photo of anthropometry

measurement of insertion and origins

Figure A.2: Experiment photo of biceps insertion measurement

Figure A.3: Experiment photo of biceps origin (long head) measurement

Figure A.4: Experiment photo of triceps insertion measurement

Figure A.5: Experiment photo of brachialis insertion measurement

Figure A.6: Experiment photo of brachialis origin measurement

measurement of muscle fascicle length

Figure A.7: Experiment photo of biceps fascicle length measurement

Figure A.8: Experiment photo of triceps fascicle length measurement

measurement of muscle group's PCSA

Figure A.9: Experiment photo of flexor's PCSA measurement

Figure A.10: Experiment photo of extensor's PCSA measurement

contraction theorem

Here we provide the basic definition and contraction theorem (adapted from [140]).

Definition: Given the system equations $\dot{x} = f(x, t)$, a region of the state space is called a contraction region if the Jacobian $\frac{df}{dx}$ is uniformly negative definite in that region.

Theorem: Given the system equation $\dot{x} = f(x, t)$ and a trajectory, all trajectories started in a ball of constant radius centered about the given trajectory and contained at all times in a contraction region, remain in that ball and converge exponentially to this trajectory.

Furthermore, global exponential convergence to the given trajectory is guaranteed if the whole state space is a contraction region.

To sum up, the above definition defines the contraction region and theorem gives the system behavior in the contraction region. For further knowledge refer to [140].

skeletal dynamics of human walking

Using Newton-Euler method, the motion equations of three-segments musculoskeletal model can be presented as:

$$\begin{bmatrix} T_1 \\ T_2 \\ T_3 \end{bmatrix} + \begin{bmatrix} M(\theta)_{11} & M(\theta)_{12} & M(\theta)_{13} \\ M(\theta)_{21} & M(\theta)_{22} & M(\theta)_{23} \\ M(\theta)_{31} & M(\theta)_{32} & M(\theta)_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} + \begin{bmatrix} C(\theta, \dot{\theta})_1 \\ C(\theta, \dot{\theta})_2 \\ C(\theta, \dot{\theta})_3 \end{bmatrix} + \begin{bmatrix} G(\theta)_1 \\ G(\theta)_2 \\ G(\theta)_3 \end{bmatrix} + \begin{bmatrix} T_L(\theta)_1 \\ T_L(\theta)_2 \\ T_L(\theta)_3 \end{bmatrix} = 0 \quad (\text{A.1})$$

The following convention applies to the notation used in above equations. Subscript 1, 2, 3 means 1) hip, knee and ankle joint respectively, when referring to angles, joint moments and joint reaction force ; or 2) thigh, shank and foot respectively, when referring to everything else. In equation A.1, θ_i is the angle of joint i . T_i represents musculotendon torques acted on the joint i . $T_L(\theta)_i$ is the torque acted on joint i due to other external forces besides gravity, which includes the disturbance torque and ground torque applied to the foot in this work. $M(\theta)$ is the inertial matrix. $C(\theta, \dot{\theta})_i$ represents the centrifugal and Coriolis torque on joint i . $G(\theta)_i$ is the gravitational torque on joint i .

$$\begin{aligned} M(\theta)_{11} = & m_1 d_1^2 + I_1 + m_2 (l_1^2 + d_2^2 + 2l_1 d_2 \cos \theta_2) + I_2 + m_3 [l_1^2 \\ & + l_2^2 + d_3^2 + 2l_1 l_2 \cos \theta_2 + 2l_1 d_3 \cos(\theta_2 + \theta_3) + 2l_2 d_3 \cos \theta_3] + I_3 \end{aligned} \quad (\text{A.2})$$

$$\begin{aligned} M(\theta)_{12} = & m_2 (d_2^2 + l_1 d_2 \cos \theta_2) + I_2 + m_3 [l_2^2 + d_3^2 \\ & + l_1 l_2 \cos \theta_2 + l_1 d_3 \cos(\theta_2 + \theta_3) + 2l_2 d_3 \cos \theta_3] + I_3 \end{aligned} \quad (\text{A.3})$$

$$M(\theta)_{13} = m_3 [d_3^2 + l_1 d_3 \cos(\theta_2 + \theta_3) + l_2 d_3 \cos \theta_3] + I_3 \quad (\text{A.4})$$

$$M(\theta)_{21} = M(\theta)_{12} \quad (\text{A.5})$$

$$M(\theta)_{22} = m_2 d_2^2 + I_2 + m_3 (l_2^2 + d_3^2 + 2l_2 d_3 \cos \theta_3) + I_3 \quad (\text{A.6})$$

$$M(\theta)_{23} = m_3 (d_3^2 + l_2 d_3 \cos \theta_3) + I_3 \quad (\text{A.7})$$

$$M(\theta)_{31} = M(\theta)_{13} \quad (\text{A.8})$$

$$M(\theta)_{32} = M(\theta)_{23} \quad (\text{A.9})$$

$$M(\theta)_{33} = m_3 d_3^2 + I_3 \quad (\text{A.10})$$

$$\begin{aligned} C(\theta, \dot{\theta})_1 = & -[(m_2 l_1 d_2 + m_3 l_1 l_2) \sin \theta_2 + m_3 l_1 d_3 \sin(\theta_2 + \theta_3)](\dot{\theta}_2^2 - 2\dot{\theta}_1 \dot{\theta}_2) \\ & -[m_3 l_1 d_3 \sin(\theta_2 + \theta_3) + m_3 l_2 d_3 \sin \theta_3] \cdot (\dot{\theta}_3^2 - 2\dot{\theta}_1 \dot{\theta}_3 + 2\dot{\theta}_2 \dot{\theta}_3) \end{aligned} \quad (\text{A.11})$$

$$\begin{aligned} C(\theta, \dot{\theta})_2 = & [(m_3 l_1 l_2 + m_2 l_1 d_2) \sin \theta_2 + m_3 l_1 d_3 \sin(\theta_2 + \theta_3)]\dot{\theta}_1^2 \\ & - m_3 l_2 d_3 \sin \theta_3 (\dot{\theta}_3^2 - 2\dot{\theta}_1 \dot{\theta}_3 + 2\dot{\theta}_2 \dot{\theta}_3) \end{aligned} \quad (\text{A.12})$$

$$\begin{aligned} C(\theta, \dot{\theta})_3 = & [m_3 l_1 d_3 \sin(\theta_2 + \theta_3) + m_3 l_2 d_3 \sin \theta_3]\dot{\theta}_1^2 \\ & + m_3 l_2 d_3 \sin \theta_3 (\dot{\theta}_2^2 - 2\dot{\theta}_1 \dot{\theta}_2) \end{aligned} \quad (\text{A.13})$$

$$\begin{aligned} G(\theta)_1 = & m_1 g d_1 \cos \theta_1 + m_2 g [l_1 \sin \theta_1 + d_2 \cos(\theta_1 + \theta_2)] \\ & + m_3 g [l_1 \sin \theta_1 + l_2 \sin(\theta_1 - \theta_2) + d_3 \sin(\theta_1 - \theta_2 - \theta_3)] \end{aligned} \quad (\text{A.14})$$

$$G(\theta)_2 = m_2 g d_2 \sin(\theta_1 - \theta_2) + m_3 g [l_2 \sin(\theta_1 - \theta_2) + d_3 \cos(\theta_1 - \theta_2 - \theta_3)] \quad (\text{A.15})$$

$$G(\theta)_3 = m_3 g d_3 \sin(\theta_1 - \theta_2 - \theta_3) \quad (\text{A.16})$$

where l_i is the length of segment i . d_i is the distance from the proximal joint of the segment i to its center of mass position. m_i is the mass of segment i . I_i is the moment of inertia of segment i . g is the gravitational constant.