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Patient-Specific Neuromusculoskeletal Models for Improving the Effectiveness of Human-Inspired Gait Rehabilitation Robots

Ye Ma

Abstract

Rehabilitation robots are widely used to assist patients with neurological disorders in performing exercise tasks. Compared with physiotherapists, gait rehabilitation robots seldom tire, are able to accomplish gait retraining precisely, and provide quantitative feedback to show the movement patterns of the patients. However, the effectiveness of robot treatment methods is still under debate. Current gait rehabilitation robots are limited in the following two aspects. Firstly, they do not have the knowledge to account for patient variability. Secondly, they do not take into account the patient’s intention and engagement in the training. Therefore, this study investigated the use of biomechanical methodologies, including gait analysis technique, three-dimensional musculoskeletal modelling and simulation technique and muscle force estimation methodologies to enhance the effectiveness of gait rehabilitation robots.

This study aims to develop neuromusculoskeletal models, which include the patient-specific musculoskeletal properties and model the patients’ effort in muscle level. Two new models are developed in this research: the patient-specific muscle force estimation model (PMFE) and the patient-specific electromyography (EMG)-driven neuromuscular model (PENm). The PMFE and the PENm predict joint moment and muscle forces through kinematic information and EMG signals, respectively.

The PMFE improves traditional inverse dynamic-static optimization model by realizing real-time calculation and ensuring good model prediction accuracy. Besides employing patient-specific musculoskeletal model for accurately modelling, the PMFE employs an analytical algorithm, the Lagrange multiplier method, in the static optimization procedure for real-time calculation. The musculoskeletal model is also simplified to one extensor and one flexor muscle around hip and knee joint for real-time calculation.
Abstract

The PMFE is evaluated by comparing the joint moments and individual muscle forces calculated via the PMFE and the computed muscle control method for healthy adolescents. Results show that the PMFE calculated joint moments and individual muscle forces accurately. As a case study of the PMFE, a patient-specific biological command based controller (PSBc) is developed based on the PMFE to control a human-inspired exoskeleton. The simulation and real-world experiment results show that the exoskeleton is controlled by the proposed PSBc with good accuracy.

The second model, the PENm makes the following improvements for predicting individual muscle forces accurately in real-time. Firstly, the PENm incorporates EMG signals from two muscles around knee joint and using minimum musculotendon parameters in the model optimization process. Secondly, a dynamic computational model is developed based on Zajac’s computation flowchart to ensure the PENm predict muscle force in real-time. Thirdly, the PENm is based on a simplified patient-specific musculoskeletal model, which provides accurate patient-specific musculotendon parameters and muscle kinematics parameters. Fourthly, a combined force-length-velocity relationship is implemented to generate accurate muscle forces. The PENm is evaluated by comparing the joint moment and muscle forces via the PENm and the inverse dynamics and EMG activations for both healthy and cerebral palsy adolescents. Results show that the PENm can predict accurate joint moment in real-time. The PENm also provide more in-depth information on muscle functions.

In summary, the design of gait rehabilitation robotic control strategies and clinical gait assessment can benefit from applications of the proposed biomechanical models. This research has collaborated with Department of Exercise Science and Shanghai Sunshine Hospital. The thesis has been published in two peer-reviewed SCI journals and presented at three international conferences.
Acknowledgements

I would like to take this opportunity to thank my supervisors, Prof. Shengquan Xie and Dr. Yanxin Zhang for their excellent guidance. They not only improved my research skills but also taught me a lot on how to be a good person. They guided me to become a more mature researcher from a layman or outsider. I also really appreciate their patience for the slow adaptation to my Ph.D. life. I am really grateful for their encouragement and always believe in me when I was sad, anxious or lost.

I sincerely thank my parents, although they are on the other side of the planet, they have always believed in me since the day I was born. Thanks to my sister and brother, their concerns are one motivation for me to move on.

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Last but not least, I would like to thank the Department of Mechanical Engineering for giving me the opportunity to pursue my degree at such a fine institution.
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Content from this publication is contained in the Chapter 4, showing the structure of the patient-specific biological command based controller and simulation evaluation.

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<td>Shengquan Xie</td>
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<td>Yanxin Zhang</td>
<td>Assist with research approach, provided manuscript revision</td>
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Content from this publication is contained in the Chapter 3, providing development of the proposed patient-specific muscle force estimation model and the model evaluation.

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Ye Ma, Shengquan Xie, Yanxin Zhang, A patient-specific EMG-driven neuromuscular model for the potential use of human-inspired gait rehabilitation robots, Computers in Biology and Medicine, Volume 70, 1: 88-98.

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Figure 1.2: A typical clinical gait laboratory. Inside the red blocks are infrared cameras and inside the blue block is the force plate. Note that the amount of infrared cameras and force plates are varied depending on applications of the lab. The picture was taken in the Biomechanics Lab of Department of Exercise Science.

Figure 1.3: The human-robot system. The solid arrows represent physical interaction (force, velocity). The hollow arrows represent cognitive interaction (sensory stimuli). The figure shows the sensory-motor control system of both human (Yellow) and the robot (Green). The red blocks are our research task, which is estimates patient’s intention from the neuromuscular system.

Figure 2.1: Key Elements of the LokomatPro. The figure is from a public domain in [83]. "The LocomatPro offer physiologic gait pattern with constant feedback and therapy assessment. It improves rehabilitation outcome by increased therapy volume and intensity, task-specific training and high patient engagement."

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<td>3D</td>
<td>Three dimensional</td>
</tr>
<tr>
<td>BASMC</td>
<td>Boundary layer augmented sliding mode position controller</td>
</tr>
<tr>
<td>BF</td>
<td>Biceps femoris muscle</td>
</tr>
<tr>
<td>BFL</td>
<td>Biceps femoris caput longum</td>
</tr>
<tr>
<td>BFS</td>
<td>Biceps femoris caput breve</td>
</tr>
<tr>
<td>CMC</td>
<td>Computed muscle control</td>
</tr>
<tr>
<td>CP</td>
<td>Cerebral palsy</td>
</tr>
<tr>
<td>DOF</td>
<td>Degree of freedom</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>FL</td>
<td>The force-length relationship of muscle fibres</td>
</tr>
<tr>
<td>FLV</td>
<td>The force-length-velocity relationship of muscle fibres</td>
</tr>
<tr>
<td>GMFCS</td>
<td>Gross motor function classification system</td>
</tr>
<tr>
<td>FSR</td>
<td>Force-sensing resistor</td>
</tr>
<tr>
<td>FV</td>
<td>The force-velocity relationship of muscle fibres</td>
</tr>
<tr>
<td>HuREx</td>
<td>Human-inspired robotic exoskeleton</td>
</tr>
<tr>
<td>LMM</td>
<td>Lagrange multiplier method</td>
</tr>
<tr>
<td>MRI</td>
<td>Magnetic resonance imaging</td>
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<td>MT</td>
<td>Musculotendon</td>
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<td>MTU</td>
<td>Musculotendon unit</td>
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<tr>
<td>PENm</td>
<td>The patient-specific EMG-driven neuromuscular model</td>
</tr>
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<td>Abbreviation</td>
<td>Description</td>
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<td>--------------</td>
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<tr>
<td>pHRI</td>
<td>Physical human-robot interaction</td>
</tr>
<tr>
<td>PMA</td>
<td>Pneumatic air muscle actuator</td>
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<td>PMFE</td>
<td>The patient-specific muscle force estimation model</td>
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<td>PPAM</td>
<td>The pleated pneumatic artificial muscle</td>
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<td>RF</td>
<td>Rectus femoris muscle</td>
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<tr>
<td>RIC</td>
<td>The robot-in-charge control strategy</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean squared error</td>
</tr>
<tr>
<td>ROM</td>
<td>Range of motion</td>
</tr>
<tr>
<td>SCI</td>
<td>Spinal cord injury</td>
</tr>
<tr>
<td>SD</td>
<td>Standard deviation</td>
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<tr>
<td>SEA</td>
<td>Hydraulic actuator and series elastic actuator</td>
</tr>
<tr>
<td>sEMG</td>
<td>Surface electromyography</td>
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<tr>
<td>SM</td>
<td>Semimembranosus muscle</td>
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<tr>
<td>SP</td>
<td>Swing phase</td>
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<td>ST</td>
<td>Semitendinosus muscle</td>
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<td>TD</td>
<td>Typically developing subjects</td>
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<tr>
<td>VI</td>
<td>Vastus intermedius muscle</td>
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<tr>
<td>VL</td>
<td>Vastus lateralis muscle</td>
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<tr>
<td>VM</td>
<td>Vastus medialis muscle</td>
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Robots are changing our lives in almost every aspect. They expand our physical abilities and compensate our physical defects. When zooming the robotic applications into gait rehabilitation, nowadays there are more and more robots being developed to help people with gait dysfunctions. Gait rehabilitation robots do not have fatigue and are able to accomplish gait retraining intelligently. Moreover, they also provide quantitative information to show the real-time status of the patients and the robots. The quantitative information is helpful for diagnosing or assessing gait dysfunctions and treatments. Standing on the foundation of previous gait rehabilitation robots, challenges remain on how to improve the effectiveness of existing robots and ensure intelligent and optimal training.
1.1 Gait

1.1.1 Gait

*Human gait*, one of the most important movements during *active daily life* (ADL), means locomotion accomplished through the limb movements of people. Gait is the most convenient traveling method for short distances. Gait efficiency depends on free joint mobility and muscle activity, which is selective in timing and intensity. Energy conservation of normal gait pattern is optimal. During gait, the upper body such as head, neck, trunk and arms are viewed as a passenger unit. Actions of the passenger unit are not essential to the normal gait pattern except for its own stability and postural integrity. The locomotor system is formed by pelvis and both lower extremities. In detail, the locomotor system includes eleven articulations: lumbosacral, bilateral hip, knee, ankle, subtalar, and metatarsophalangeal joints. Motions of each limb are controlled by 57 muscles acting in a selective fashion. The skeletal segments (pelvis, thigh, shank, foot, and toes) serve as levers and are characterized by mass, length, center of mass, moment of inertia and so forth.

People use a repetitive gait pattern to move the body forward while simultaneously maintain stance stability. It involves alternative sequences in which the body is supported first by one limb and then by the other limb. The period of support is referred to as the *stance phase*, and nonsupport period is referred to as the *swing phase*. A single sequence of these events is called one *gait cycle* (GC). As illustrated in Figure 1.1, a normal gait cycle (stance phase and swing phase) is subdivided into eight functional patterns according to the sequence of the floor contact. These eight sub-phases are initial contact (0%~2%), load response (0%~10%), mid-stance (10%~30%) and terminal stance (30%~50%), pre-swing (50%~60%), initial swing (60%~73%), mid-swing (73%~87%) and terminal swing (87%~100%). An entire gait cycle accomplishes three tasks, which are weight acceptance, single limb
support, and limb advancement. Weight acceptance and single limb support are achieved by stance phase. The limb advancement is realized by swing phase. Each of the eight gait phases has a functional objective and a pattern of selective synergistic motions to achieve this goal. Specifically, initial contact starts stance phase with a heel rocker. During the loading response phase, the locomotor system accomplishes three tasks: shock absorption, weight-bearing, and stability maintenance. During the mid-stance phase, the locomotor system progresses itself over the stationary limb and maintain the stability of the passenger system. During the terminal stance phase, the locomotor system progresses itself over the supporting foot. During the pre-swing phase, the system positions the limb for swing. During the initial swing phase, the foot is lifted from the floor and the limb is progressed by hip flexion and increased knee flexion. During the mid-swing and terminal swing phases, the locomotor system completes the limb advancement and prepares the limb for next stance phase.
Figure 1.1: Gait simulation over a gait cycle from side and anterior views. The figure illustrates the gait cycle for the right limb. Phases of gait and their corresponding functions are demonstrated in this figure. All images are presented through a musculoskeletal modeling and simulation software [1].

### 1.1.2 Gait analysis techniques

The history of gait analysis can stem back to ancient Greece. Aristotle reported the earliest research on human walking in his book “De Motu Animalium”, which observed that the trunk and head move up and down during walking. Due to the limitation of technology, gait study has been limited to descriptive measures for a long period until the 19th century. Weber Brothers (1836) published “The Mechanics of the Human Walking Apparatus”, which recorded the first detailed observational measurements of walking.

With the advances of modern technology, gait analysis techniques are rapidly improving. In the late 1960s, the first television-based motion capture system was
developed at the Delft University of Technology in The Netherlands [4]. In the past few decades, there have been several kinds of motion capture systems developed: video cameras systems, magnetic systems, optoelectronic measurement systems, and optical marker systems using infrared cameras. For gait analysis, optical marker systems are the most popular option and are used in most gait labs due to its high precision and good usability [5]. Nowadays, gait analysis has been accepted as a quantitative functional assessment for patients with neurological disorders, e.g. children with cerebral palsy, and is used to evaluate the efficacy of various treatment protocols. A standard gait analysis approach is to record motion data using a motion capture system and then using inverse dynamics to calculate joint angles, forces and moments. Figure 1.2 shows a typical optical marker system using infrared camera mounted permanently from the ceiling in a clinical gait laboratory. Details of this technique are described in Chapter 6.

Figure 1.2: A typical clinical gait laboratory. Inside the red blocks are infrared cameras and inside the blue block is the force plate. Note that the amount of infrared cameras and force plates are varied depending on applications of the lab. The picture was taken in the Biomechanics Lab of Department of Exercise Science.
Dynamic *electromyography* is another gait analysis technique. The *electromyogram* (EMG) is the electrical signal travel through the muscles and adjacent soft tissues during muscle action. With appropriate instrumentation, the EMG signals can be recorded and analysed to determine the timing and intensity of the muscular effort. With complex EMG-driven and musculoskeletal models, one can also estimate the resulting muscle forces from EMG signals.

Normally, there are three types of EMG signal electrodes: *needle, fine-wire, and surface*. Needles are too insecure and uncomfortable. Therefore they are seldom be used in gait analysis. Fine-wire electrodes are stable means of recording EMG signals directly from muscle. Those electrodes are also quite “selectivity”, which means the EMG data can be isolated to the target muscle with appropriate filtering. They are regarded as “gold standard” for recording “deep muscles” [6]. Surface EMG electrodes are metal discs taped to the skin and they record muscle activity from the surface of the muscle [7]. They are widely used in gait analysis because of the comfort and non-invasive. These electrodes are limited to recording surface EMG signals from superficial muscles. The signals are influenced by the depth of the subcutaneous tissue at the site of the recording, which can be highly variable from different subjects [5]. Combine with EMG recording system, a complex EMG analysis system also includes signal amplification, filtering technics, signal transmission, as well as EMG-driven modelling.

### 1. 2 Gait dysfunction and rehabilitation

#### 1.2.1 Gait dysfunction

*Gait dysfunction*, or gait abnormality, is a deviation from normal gait. Patients with gait dysfunction tend to preserve the optimal energy conservation capacity or part of
the capacity even in severe impairment. The resulting walking pattern is a mixture of normal and abnormal motions that differ in significance [8].

Gait dysfunctions are caused by problems in the nervous system or the musculoskeletal system. The abnormalities imposing on the mechanics of gait fall into four functional categories: deformity, muscle weakness, impaired control, and pain [5]. Deformity appears when the tissues could not provide sufficient passive mobility for the patient to attain normal postures and range of motions. It is normally caused by contracture. Muscle weakness may be caused by muscular atrophy as well as neurological impairment. When it is a lower motor neuron disease or muscular pathology, the patients would adapt themselves by substitution. Sensory loss such as the proprioceptive impairment prevents the patient knowing the position of the hip, knee, ankle, foot and the contact with the floor. Persons with intact motor control may substitute by keeping the knee locked or hit the floor with extra vigor to emphasize the moment of contact. Joint distension related to trauma or arthritis usually along with musculoskeletal pain. It is due to excessive tissue tension. Patients with a central neurological lesion (brain or spinal cord) result in spastic paralysis (impaired motion control). People with spasticity overreact to stretch.

The most common causes of spastic gait are neurological disorders such as stroke [9], incomplete spinal cord injury (SCI) [10, 11], cerebral palsy (CP) [12, 13], brain injury [14] and multiple sclerosis [15]. Hundreds of millions of people are affected by neurological disorders, e.g. stroke and SCI. Stroke was the second most frequent cause of death worldwide, accounting for 6.2 million deaths in 2011. Approximately 17 million people survived in stroke in 2010 [16]. In New Zealand, stroke is the third largest killer and there are around 60,000 stroke survivors in New Zealand. The majority of them are disabled and need significant daily support [17]. The number of new case of SCI ranges from 10.4 to 83 people per million per year [10]. In the
United States, the incidence of SCI is around 12,000 cases per year [18]. In China, the incidence is approximately 60,000 per year [19]. The estimated number of people living with SCI in the world ranges from 236 to 4187 per million [10]. Thus, the demand for gait rehabilitation is huge. It is encouraged to develop effective gait rehabilitation therapy for those patients survived from neurological disorders.

1.2.2 Gait rehabilitation

Gait rehabilitation treatments are necessary for patients with neurological disorders. Generally speaking, there are two main theories underlying the neurological rehabilitation: the compensation model and the activity-dependent neural adaptation model [20]. The first model assumes that the nervous system is hard-wired and irreparable. Thus, clinicians use compensation as a rehabilitation strategy for non-remediable deficits of strength, voluntary motor control, sensation, or balance. The compensation based strategy is to teach new movement strategies using braces or assistive devices (e.g. wheelchairs [21]). This approach enables, rather than cues, disablement. More and more evidence support an emerging paradigm shift for the rehabilitation of walking after neurological disorders from compensation for deficits to activity-dependent neural adaptation and training [22].

Neurorehabilitation of human gait is about the recovery capacity of the central nerve system (CNS) [22]. Some neuroscientists have investigated the capacity of CNS to learn, to respond, and to control walking both in animals and humans. Recovery in the CNS does not involve generation of new neurons, but it does involve the formation of new synapses. Synaptogenesis is enhanced with activity. This reorganization underlies processes associated with motor learning and memory [23, 24]. Other attempts to examine the CNS have focused on the ability of the spinal cord to compensate for the removal of selected inputs or pathways. Based on the activity-dependent neural adaptation model (the recovery model) [25, 26], much
evidence supports that [27, 28] *task-oriented repetitive training* can improve motor performance for patients with neurological or orthopaedic lesions [29-37].

There are growing evidence supporting that task-oriented repetitive training [27, 28] from the *physical therapy* (PT) and the *robotic therapy* [38] can improve motor performance for patients with neurological or orthopedic lesions [29-37] based on the recovery model. Comparing with PT, robotic gait rehabilitation solution is better because it is precise, tireless and also can quantitatively assess the effectiveness of gait recovery with high accuracy [39]. Preliminary studies have found that individuals who receive the robotic task-specific gait training following stroke [40] and spinal cord injury [41-43] demonstrate improved EMG activity during locomotion [44], walk more symmetrically [45], are able to bear more weight on their legs [41], and experience higher returns in functional walking ability when compared to patients who receive conventional gait training [42]. Furthermore, evidence also showed that the robotic training paradigms that enforce a fixed kinematic control was suboptimal [34, 46] or even counterproductive [47] for rehabilitative training because they abolish variability, and intrinsic property of neuromuscular control, which is likely to reduce the activity of the spinal neural control circuits that control locomotion [48-50]. Thus, appropriately recreating the feature of neural control may be essential for the development of effective robotic control algorithms for assisting the post-neurological injury neuromuscular system in learning a motor task.

### 1.3 The human-robot gait rehabilitation system

According to the neuromuscular control theory of gait and the clinical evidence, the optimal control strategies have the following requirements: task-specificity [51], repeatability, intensity, optimal physical and mental engagement, compliant and self-initiative [52]. Two general requirements are introduced into the robotic gait
rehabilitation, which are realizing normal walking patterns and engaging the patient’s voluntary motion. Because of the closely physically and cognitively interaction, the patient and the gait rehabilitation robot should be viewed as an integrated system, the human-robot system, which works in an intuitive and synergetic way. Optimal control of the human-robot system requires understanding the dynamic behaviors, sensory system, motor control system as well as the actuation system simultaneously of both the human and the robot.

Figure 1.3: The human-robot system. The solid arrows represent physical interaction (force, velocity). The hollow arrows represent cognitive interaction (sensory stimuli). The figure shows the sensory-motor control system of both human (Yellow) and the robot (Green). The red blocks are our research task, which is estimates patient’s intention from the neuromuscular system.

Figure 1.3 shows the sensory-motor system of both human and robot. The locomotion of human is optimised by the central nerve system (CNS). At the supraspinal level, modulation of locomotor patterns is generated and both the central pattern generator (CPG) and reflex mechanisms (motor neuron and sensory neuron)
are regulated. The reflex mechanisms take in charge of efferent activation and afferent feedback. The CPG, a network of spinal interneurons, generates basic motor patterns. The basic motor patterns are also regulated by the afferent feedback. The reflex mechanisms increase the efficiency of gait and stabilise posture when there are unexpected perturbations. The efferent nerves (motor neurons) pass the motor command to individual muscles, generating forces and moments about one or more joints. The afferent nerves (sensory neurons), gather information from the musculoskeletal system and pass them to the CNS.

Similarly, the “sensory motor system” of the gait rehabilitation robot is the controller-actuator system. Robot structure and actuators are the “musculoskeletal system” of the robot, generating desired power to fulfil movements. The controller is served as the “CNS” of the robot, regulating the actuator under the control strategy. Sensors mounted on the robots are similar as the sensory neurons, gathering information about robotic states and giving feedback to the robot controller. Ideally, an intelligent control system for gait rehabilitation robot includes three levels: intention estimation, translation from intention to robot state, and the actuator control. At the high level of the robot controller, it recognises the patient’s locomotive intent. The middle level of the controller translates the movement intention to robot states for the lower level of the controller, the actuator controller, to track. The actuator controller computes errors regarding to current robot states and then sends commands to the actuators to reduce the error. Finally, the gait rehabilitation robot is actuated to conduct the control commands to fulfil the task. Normally, a robot is controlled by at least the low-level controller, the actuator controller. More and more high-level controllers are developed to take into account patient’s intention and provide more engaged gait rehabilitation training.
As illustrated in Figure 1.3, the human, gait rehabilitation robot, and the environment are interacting with each other physically and cognitively. Ideally, the control of the human-robot system begins with patient’s motion intention, from which the patient’s physiological states are interpreted. The traditional states (the so-called “intention”) are patient’s kinetic states (such as positions, velocities and accelerations of each joint) and kinematics states (such as the moments of each joint, ground reaction forces, and the interaction forces between human and robot) [53-56]. Gait rehabilitation robots, who are providing optimal and intelligent training therapy, need to understand the sensory-motor system of human and the knowledge of how the locomotion is nominally controlled by human. Therefore, the robots can obtain the insight information of motor control and tissue loading on muscle level. Unfortunately, current robots do not have such ability of estimating patients’ intention through their neuromusculoskeletal system, which motivates this study.

### 1.4 Gait rehabilitation robots and their control strategies

Due to the close interaction between the patient and the robot, the priority of the robot is the safety of patients. In addition, according to the neurological rehabilitation theory, an optimal gait rehabilitation system should take into account motor control or patient’s intention.

#### 1.4.1 Gait rehabilitation robots

Various gait rehabilitation robots have been developed for improving patient’s locomotion following neurological damages. Most state-of-art rehabilitation robots interact with patients closely, which imposes strict requirements on such robots as regards safety and dependability [57, 58]. Three types of robots are involved regarding to robot mechanisms, which are treadmill training gait rehabilitation
robots [29, 59-61], end-effector gait rehabilitation robots [62-64], and ambulatory gait trainer [65-67].

The most successful commercially available gait rehabilitation robot is Locomat [29, 59, 68]. It is a bilateral robot working with a treadmill and a body weight support system to move patient’s leg in the sagittal plane. The Locomat actuates the patient’s hip and knee joints with linear drivers integrating with an exoskeleton structure. The passive foot lifters help with ankle dorsiflexion during the swing phase. The Locomat provides different modes of rehabilitation training. Besides following predefined trajectories for limbs, the Locomat also performs patient-corporative control to take into account the “patient’s intention”. Augmented performance feedback is also included to ensure more intuitive training for patients.

Nowadays, human-inspired gait rehabilitation robots are popular for more integration between the robot and the patient. Such kinds of robots are inspired by human musculoskeletal system and mimic the antagonistic actuators around the joints of lower limbs for producing an intrinsically compliant behaviour and to work in harmony with patients.

KNEXO [69, 70] is one of the human-inspired robots for gait rehabilitation. It employs antagonistic configurations of pleated pneumatic artificial muscles (PPAM) as actuators, which mimic the muscle arrangement of the human body. The actuator forces from both extensor and flexor are transferred to the joint using a pulley-and-belt system or direct connection through fixed levers. This actuation system ensures built-in compliant behaviour and good torque matching. KNEXO uses a proxy-based sliding mode controller as a trajectory tracking strategy for SCI patients with poor motor control. The controller realized accurate tracking and smooth, safe recovery from large position errors. A more comprehensive literature review on gait rehabilitation robots is presented in Chapter 2.
1.4.2 Control strategies of gait rehabilitation robots

As mentioned before, hundreds of control strategies have been developed to cope with the physically interacted gait rehabilitation robot. Most of the controllers mentioned the properties such as “assist-as-needed”, “compliance”, “robust”, and “safe”. Generally, “compliance” is the most important. Other properties are realized by being compliant via control strategies, actuation system or both of them. Controllers can be categorized into the following four groups based upon how voluntary the patient’s interaction with the robot is: robot-in-charge control, patient-robot-cooperative control, patient-in-charge control and challenge-based control. All of these control strategies represent the high-level approach to provoke motor plasticity. For most robots, the “high-level” algorithms are supported by “low-level” controllers, which directly control the actuators through various forces, positions, impedance, admittance, stiffness control algorithms and so forth.

In the robot-in-charge control strategies, no intention or voluntary movement on the part of the patient is involved. They are suitable for patients in the very early stage of rehabilitation or for patients who are badly injured. The patient-robot-cooperative control strategies are the most highly developed strategy. Researchers regard the patient-robot-cooperative strategies as to recognize the patient’s movement intention and motor abilities in terms of muscular effort, feedback the information to the patient and adapt the robot assistance to the patient’s contribution. In this mode the robotic devices complement the patient’s intention and voluntary efforts rather than imposing any predefined movements or inflexible routines. The patient-in-charge control strategies serve as a baseline for evaluating the effects of robotic assistance, recording target trajectories, familiarizing users with the device and recording unassisted motions [53, 61]. Challenge-based control strategies are in some ways the opposite of the robot-in-charge or patient-robot-cooperative controllers because they
make the movement tasks more difficult and challenging. Challenge-based control and patient-robot-cooperative control can be viewed as parts of a continuum of task difficulty, which is designed to challenge the patient optimally [71]. A more comprehensive literature review on control strategies is reported in Chapter 2.

1.4.3 Challenges on designing and controlling of gait rehabilitation robots

Because of the close interaction between the patient and the robot, controlling the human-robot system requires the understanding of the dynamic behaviours of both the patient and the robot. In the past twenty years, a lot of efforts have been given to cope with the requirements for closely physical human-robot interaction (pHRI). The entire control system, which includes system dynamic modelling, reference generation, biological interaction, lower level actuator controller, became more and more intelligent, interactive, safe, nature and compliant. Although some improvements have been made for gait rehabilitation robots, there are several existing challenges in the following aspects: dynamic modelling of the human-robot system, desired state generation such as joint trajectory, human’s intention recognition, and the lower level controller design. As showed in Figure 1.2, human’s intention recognition (for some strategy, it works together with the system dynamic modelling) works in the first level to take into account human’s intention; the dynamic modelling and desired state generation works in the middle level to convert patient’s intention to desired robot states for lower level controller. This thesis deals with challenges in the first three parts of the control strategies.

Challenges about dynamic modelling of the human-robot system

In a physical human-robot interaction situation, it is necessary to model the dynamic behaviour of both the robot and the patient. In general, three-segment models (representing thigh, shank and foot) are used to identify the dynamic behaviours of
the gait rehabilitation robot and human lower limbs. Torso is assumed to be in a fixed position. Segments are modelled as mass, moments of inertia about their centre of gravity and so forth. Dynamic behaviour is described using the dynamic equation (1.1) [61, 72].

\[ M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + P(\theta) = T_h + T_r \]  

(1.1)

Here \( M \) is an inertia matrix and is a function of \( \theta \), which is the joint moment of the respective degree of freedom (DOF). \( C(\theta, \dot{\theta})\dot{\theta} \) is a centripetal and coriolis matrix. \( P \) is a function of \( \theta \) only, which normally is the gravity factor. \( T_h \) is the torque vector from the patient. \( T_r \) is the torque vector from the robot.

In modelling the human-robot system, the inertia matrix and the centripetal and coriolis matrices for the respective DOFs need to be as accurate as possible. An accurate model of the robot can be obtained by experimental configurations. For example, the mass, moment parameters, inertial parameters, stiffness torques, damping and kinematic friction torques are able to be identified via static experiments and dynamic experiments based on the least-squares estimation [73]. However, accurately modelling the human movement is challenging. The mass and inertia characteristics of the main segments of the human body are normally obtained from existing anthropometric databases [74]. The geometric values from the subject can be measured or obtained by some regression equations [75]. This introduces uncertainties in the calculation of the kinetic parameters. More importantly, joint moments calculated by the inverse dynamic approach only represent the net effect of muscle activity at a joint [76], not individual muscle functions. In the case of muscle co-contraction, the net muscle moment (difference between the moment for both agonist and antagonistic muscles as they have opposite directions) can be very small and the active muscle contributions cannot be indicated. This is a major limitation.
Challenges about determining reference trajectories of joints

Target trajectory is an important determinant of the assistive environment displayed by the device. How this trajectory should be determined is an ongoing research topic in robotic controller design. Reference trajectories are often obtained from the motion profiles of healthy subjects [29], whether scalable or non-scalable. However, non-patient-specific reference trajectories have been proven to be sub-optimal [77]. For superior rehabilitation performance and patients’ comfort, user specific reference trajectories recorded from the patient are required [78]. Some attempts have been made to generate patient-specific reference trajectories such as scaling the recorded reference gait trajectory in time, amplitude offset and range [68] or record patient’s movement during different tasks from the motion measuring system of the robots [61, 67]. These captured the patients’ motion patterns in different situations and these were afterwards analysed to obtain patient-specific reference trajectories. Nevertheless, this is very difficult, especially for severely bilaterally and unilaterally impaired subjects. A better approach to obtain optimal trajectories is needed.

Challenges about detecting of movement intention

To improve the performance of gait rehabilitation robots, the robot system should be able to take into account patients’ own intention, voluntary movements, and active muscle contraction efforts. Therefore, there will be more physiological and variable sensory input to the CNS. This solution has the potential to lead to a better rehabilitation of such disorders related to CNS [79]. Even though some attempts have been made in patient’s intention detection, challenges still exist.

The most widely used intention detection methodologies are based on kinematic and kinetic analysis: (1) kinematic parameters such as position, velocity and acceleration of the human or the robot (using the inverse dynamic model to deduce the force exerted by the human), (2) the interaction force measurement, and (3) the ground
reaction force measurement and detection of the patient’s phase status (swing phase or stance phase for walking and running) [53-56]. Even though these methodologies can estimate the human’s effort by joint torque, there is little information about motor control or individual muscle status. In other words, true patient’s intention has seldom been used in gait rehabilitation robots.

1.5 The physiological perspective

A review from a physiologist’s perspective [80] had made the conclusion that the design of future robotic devices can be improved by exploiting the biomechanical principles of human locomotion because it reduces the metabolic energy expenditure of the user while wearing the device and minimize the power requirements for actuating the exoskeleton. Furthermore, a reciprocal potential exists for robotic exoskeletons to advance our understanding of human locomotor physiology. It is imperative that engineers and physiologists work together in the studies on the robotic exoskeleton for human locomotion [80].

Musculoskeletal modelling combined with gait analysis and assessment techniques have been used to generate patient-specific musculoskeletal models as well as patient-specific joint trajectories [81]. These techniques can be employed to investigate the kinetic, kinematic or muscle function properties of human movements. Physiological muscle force estimation methodologies, such as the optimization based algorithm or EMG-driven models, providing in-depth information on muscle functions, which are helpful in determining movement intention at the muscle level. The control and assessment of rehabilitation robots can both benefit from these techniques. A more comprehensive literature review on biomechanical models is reported in Chapter 2.
1.6 Research objectives

Based on the discussion of the control strategies, in order to improve the effectiveness of the rehabilitation robot, it’s needed to incorporate the patient’s intention, anthropometric and anatomy information, musculoskeletal properties and also the biomechanical principles of human locomotion. As showed in Figure 1.3, this research focuses on estimating patient’s intention through the neuromusculoskeletal system. Therefore, the general purpose of this project is to develop neuromusculoskeletal models with the potential of enhancing the effectiveness of human-inspired gait rehabilitation robots. The human-inspired gait rehabilitation robots are defined as follows [82]: (1) the robots are designed for gait rehabilitation, and (2) the actuation system mimics the human musculoskeletal system, i.e. two antagonistically coupled compliant actuators actuate one joint. Neuromusculoskeletal methodologies including three-dimensional (3D) musculoskeletal models, inverse dynamics-based static optimisation, electromyography (EMG)-driven model and gait analysis technique are investigated for achieving this goal. Four studies are conducted.

Study 1: Patient-specific muscle force estimation model for the potential use of human-inspired gait rehabilitation robots

The purpose of this study is to develop a patient-specific muscle force estimation model (PMFE) for the potential use of human-inspired gait rehabilitation robots. This model employs an inverse dynamics-static optimization algorithm based on a computer-based musculoskeletal model, which provides patient-specific anthropometric parameters and muscle moment arms. Joint moments and muscle forces estimated by Inverse Dynamic tool (ID) of OpenSim and the computed muscle control (CMC) method respectively are used to evaluate the PMFE. The evaluation
uses gait analysis data including lower limb kinematics and EMG signals from selected muscles from six healthy adolescents at their comfortable speeds.

Study 2: Patient-specific biological command based controller for human-inspired robotic gait rehabilitation

The purpose of this study is to develop a patient-specific biological command based controller (PSBc) for a human-inspired gait rehabilitation robot. Based on a patient’s musculoskeletal model, the PSBc consists of two main components: the PMFE developed in study 1 and a PMFE-based feedforward controller. The PMFE-based feedforward controller serves as the lower level force controller for pneumatic muscle actuators. The PSBc is evaluated via a computer simulation and an experimental study using a human-inspired gait swing robot.

Study 3: Patient-specific EMG-driven neuromuscular model for real-time control of gait rehabilitation robots

The purpose of this study is to develop a patient-specific electromyography (EMG)-driven neuromuscular model (PENm) for potential use with human-inspired gait rehabilitation robots. The PENm predicts the movement intention (i.e., joint moments and individual muscle forces) ahead of the actual movement because of the inherent property of sEMG. The PENm improves the EMG-driven models by decreasing the calculation time and giving good prediction accuracy. To ensure efficiency of the calculation, the PENm is simplified into two EMG channels around one joint with minimal physiological parameters. A dynamic computation model is developed to achieve real-time calculation. To ensure the accuracy of the calculation, patient-specific muscle kinematics information such as the musculotendon lengths and the muscle moment arms during the entire gait cycle is employed, based on the patient-specific
musculoskeletal model. Moreover, an improved force-length-velocity relationship is implemented to generate accurate muscle forces. Gait analysis data including kinematics, ground reaction forces and raw EMG signals from six adolescents at three different speeds are used to evaluate the PENm.

Study 4: Patient-specific EMG-driven neuromuscular model for cerebral palsy patients

The purpose of this study is to apply PENm in investigating the joint moment and muscle functions for cerebral palsy patients. The PENm evaluation employs the gait analysis technique using a three-dimensional motion capture system combined with EMG recording devices as well as the musculoskeletal modelling technique. Patient-specific musculoskeletal models for cerebral palsy patients and reference joint angles and moments are obtained via the gait analysis technique. Four cerebral palsy patients (one girl and three boys), aged between 12 and 15 years old, with the gross motor function classification system ranked at class I, participated in this study.

1.7 Thesis outline

This chapter briefly introduced the general research purpose and main methods of this thesis. Including this chapter, the thesis is composed of seven chapters in total. Chapter 2 reviews related work and describes the background of this study. The review summarizes current gait rehabilitation robots and their limitations regarding to close interaction between the patient and the robot. It also reviews neuromusculoskeletal methodologies, which have the potential to improve the effectiveness of current gait rehabilitation control systems. Chapter 3 and Chapter 5 present two neuromusculoskeletal models, which estimate individual muscle forces via optimization algorithm and EMG-driven models, respectively. Both of these two models are built on patient-specific musculoskeletal models. Chapter 4 presents a
case study of employing the muscle force estimation model via static optimization.
The proposed biological command controller translates patient’s intention and then passes to the actuator controller to achieve gait training tasks. Chapter 6 evaluates the EMG-driven model for muscle force estimation model on cerebral palsy patients and explores the potential of the proposed EMG-driven model in gait assessment. The final chapter, Chapter 7, summarizes the key findings and the contributions of this study. The directions for future work are further discussed.

1.8 Summary

This chapter firstly discussed the basics of gait dysfunction and rehabilitation and the benefit of gait rehabilitation robots. The human-robot gait rehabilitation system was presented. The relationship and interactions between the sensory-motor system of human and robot were stated. Limitations of current control strategies of gait rehabilitation robots were identified and the physiological methodologies such as gait analysis technique, musculoskeletal modelling and simulation technique, muscle force estimation via static optimization and EMG-driven modelling were suggested as potential solutions for improving the effectiveness of gait rehabilitation robots. Most importantly, this chapter listed four main research objectives, which would be introduced in detail in the following chapters.
Literature Review

This chapter presents a review of the literature on gait rehabilitation robots with a focus on control strategies and neuromusculoskeletal models. The purpose of this review is to summarize previous research in these two areas, identify the limitations of current control strategies, and explore how neuromusculoskeletal models can be developed to improve the outcome effectiveness of gait rehabilitation robots.

2.1 Gait rehabilitation robots

The attempts of using machine to assist gait rehabilitation can date back to 1986. Barbeau, Wainberg and Finch [83] developed the body weight support (BWS) training strategy to provide task-specific repetitively gait retraining. With the help of the body weight support system, patients with gait disorders are able to practice desired gait patterns repetitively. Therapists guide patient’s lower limb to ensure they follow desired gait patterns during the entire gait training session. Thus, the effectiveness of this approach mostly depends on therapists. Fatigue and gait
rehabilitation experience influence the training outcome. Besides, manually moving the patient’s leg for each gait cycle cannot guarantee identical and optimal.

Gait rehabilitation robots are solutions of the aforementioned problems. Lokomat [29, 84], LOPES [60], KNEXO [53] or PAM&POGO [61] are examples of *treadmill training gait rehabilitation robots*. Normally, such robots are composed of gait rehabilitation mechanisms and trunk/pelvis manipulator. They employ actuated robotic legs to replace therapists. The robots provide guidance of patient’s lower limb and ensure that patients could walk using desired gait patterns for each gait cycle. Figure 2.1 shows a patient performing gait training on a Locomat.

![Key Elements of the LokomatPro](image)

Figure 2.1: Key Elements of the LokomatPro. The figure is from a public domain in [85]. "The LocomatPro offer physiologic gait pattern with constant feedback and therapy assessment. It improves rehabilitation outcome by increased therapy volume and intensity, task-specific training and high patient engagement."
End-effector gait rehabilitation robots, such as GaitTrainer [86], HapticTrainer [63, 87] or G-EO system [64], consist of two separate footplates to support patients and move patients’ leg following desired gait patterns. The footplates are actuated and programmable, which could simulate fixed stance and swing phase of the gait cycle and furthermore simulate walking on different scenarios.

Ambulatory gait rehabilitation robots such as the WalkTrainer [67] consist of mobile bases for body weight support. The WalkTrainer also includes trunk/pelvis support system and actuated exoskeleton. Lower limb joints of the WalkTrainer are powered and the exoskeletons move the patient’s lower limb according to gait training protocols.

Among all those robots, human-inspired gait rehabilitation robots mimic the human musculoskeletal system using antagonistic muscle groups actuating one joint. The human-inspired gait rehabilitation robots are compliant, safe and have the potential to realize optimal gait rehabilitation [60, 70, 88].

As mentioned in Chapter 1, current gait rehabilitation robots integrate with the patient both physically and cognitively. The robot structure and actuation system (Figure 1.2), similar with human’s musculoskeletal system, are controlled by robot sensory-control system. In order to control the robot effectively, the actuation system and sensory system are needed to be investigated.

### 2.1.1 Actuation system

There are mainly four kinds of actuators applied in gait rehabilitation robots. These are direct-current (DC) motor, pneumatic air muscle actuator (PMA), hydraulic actuator and series elastic actuator (SEA). The DC motors are the most common types of actuators, relying on the forces produced by magnetic fields. They are widely used in several areas because they are easy to be controlled and can be very
compact. For example, the assistance exoskeleton, HAL, actuates hip and knee joints using DC motors to generate the assistive torque at each joint [89]. For some non-ambulatory exoskeleton systems, e.g. Lokomat [84], Gait Trainer [86], or Haptic walker [90], they employ DC motors as actuators. These systems are extremely heavy and are not suitable for zero-impedance training due to their inertia.

The close physical interaction of gait rehabilitation robots with patients requires the actuation systems to be inherently compliant. Pneumatic, hydraulic and series-elastic actuators are all potentially suitable. Pneumatic actuators, e.g. pneumatic muscle actuators (PMA), are employed in rehabilitation robots [53, 91] because of the relatively large power to weight ratio and the compliant property. The major problems of pneumatic artificial muscles are the valve control and the need for pressurized air. The pressurized air requires compressors and thus limiting portability [92]. Moreover, the noise during venting is significant and causes severe distraction and discomfort to users [93]. The KNEXO [69, 70] employs the antagonistic configuration of a pleated pneumatic artificial muscle (PPAM) combined with a four-bar linkage mechanical system to realize compliant actuator behaviour. The PPAM is a lightweight, air-powered actuator that generates linear motion. Its core element is a reinforced pleated membrane that expands radially and contracts axially when pressurized, while exerting a pulling force in the longitudinal direction [69]. Hydraulic actuators offer large forces at better power to weight ratios than pneumatics but in general need a relatively heavy weight compressor. For instance, the BLEEX uses linear hydraulic actuators [94, 95]. POGO & PAM are pneumatically operated gait orthosis and pelvic assist manipulators which are inherently compliant and allow naturalistic motion during treadmill walking. They are designed to manipulate both the pelvis and the legs. Series elastic actuators introduce springs into traditional motors to provide compliant behaviour. LOPES [60] is a bilateral gait rehabilitation robot containing three rotational joints actuated
by Bowden cable-driven series-elastic actuators. The robot allows bidirectional mechanical interaction between the robot and the patient and can also follow or to guide the patient. A summary of actuators applied in gait rehabilitation robots are listed in Table 2.1.

### 2.1.2 Sensory system

The sensory systems of gait rehabilitation robots provide information of robotic status. The information includes position, velocity, or acceleration of the joints or segments. The information also involves the interaction with the environment (patient or ground) such as the interaction torque, ground reaction force, or biological information representing patient’s intention directly or indirectly. A summary of sensors used in gait rehabilitation robots is listed in Table 2.1.

Position sensors are used to detect kinematic information from the gait rehabilitation robots [29, 69, 70, 72, 94, 95] and the patients using them [72, 94, 95]. For example, joint angles are measured by potentiometers of Locomat [29], high-resolution incremental encoders (Avagotech AEDEA 3300-TE1) of KNEXO [69, 70] and rotary encoders of HAL [89]. On BLEEX an encoder [72, 94, 95] is used on each joint to measure joint angles in the sagittal plane directly.

Force sensors mounted between patients and robots are able to provide interaction forces [29, 60, 72, 94, 95]. Force sensors are also used to extract the subject’s active joint moment from joint reaction torque and interaction torque [29]. Force sensors combined with a motion capture system (e.g. in the LOPEX [60]), are able to determine the impedance behaviour.

*Foot-sole sensors* (FSS) [60, 72, 94, 95], *force-sensing resistors* (FSR) [69, 70], or *floor reaction force sensors* (FRF) [89] are used to detect ground reaction forces under the foot. These sensors are used to determine patients’ gait phases (e.g.,
LOPEX [60] or BLEEX [72, 94, 95], or to synchronize gait cycle initiation and duration of the patient (e.g., KNEXO [69, 70]).

Other sensors provide further crucial information for the control schemes. For example, EMG sensors are used to detect muscle activity. This can be used for directly controlling [89], monitoring or assessing the robot [60]. For example, each PPAM of KNEXO [69, 70] is equipped with a gauge pressure sensor. Combined with the pressure-regulating valve, actuators are able to be controlled by pressure.

Table 2.1: Examples of the actuators and sensors employed in the gait rehabilitation robots

<table>
<thead>
<tr>
<th>Robots</th>
<th>Actuators</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Joint angles</td>
</tr>
<tr>
<td>Locomat [29]</td>
<td>DC motors</td>
<td>Potentiometers</td>
</tr>
<tr>
<td>LOPES [60]</td>
<td>PMA</td>
<td>LED based motion capture system</td>
</tr>
<tr>
<td>KNEXO [69, 70]</td>
<td>PPAM</td>
<td>High resolution incremental encoders</td>
</tr>
<tr>
<td>BLEEX [94, 95]</td>
<td>Hydraulic actuators</td>
<td>Position encoders (on BLEEX)</td>
</tr>
<tr>
<td>HAL [89]</td>
<td>DC motor</td>
<td>Rotary encoders</td>
</tr>
</tbody>
</table>

Abbreviations: FSS: foot-sole sensors; FSR: force sensing resistors; FRF: floor reaction force; EMG: electromyography
2.2 Control strategies for gait rehabilitation robots

Many control strategies have been developed for rehabilitation robots. Controllers can be categorized into the following four groups based upon how voluntary the patient’s interaction with the robot is: robot-in-charge control strategies (RIC), patient-robot-cooperative control strategies (PRC), patient-in-charge control strategies (PIC), and challenge-based control strategy. These strategies represent the high-level strategies to provoke motor plasticity. For most robots, the high-level control strategies are supported by low-level controllers, i.e. the actuator controllers, which directly control the actuators through forces, positions, impedance, admittance, stiffness and so forth.

The RIC strategies involve no intention or voluntary movements of the patients. The PRC strategies are able to enable the robotic devices complement patients’ voluntary efforts rather than impose any predefined movements or inflexible routines. The PIC strategies, in which the patient move voluntarily and the robots are passive, refer to affiliated control modes. PIC can also serve as a baseline for evaluating the effects of robotic assistance, recording target trajectories, familiarizing users with the device and recording unassisted motions [53, 61]. Challenge-based control strategies are the opposite of the RIC strategies and PRC strategies. They make the training tasks more difficult and challenging.

2.2.1 Reference trajectory generation

Reference trajectories are important for controlling gait rehabilitation robots. Methods of generating reference trajectories are presented in this section.
Usually, reference trajectories are obtained from motion profiles of healthy subjects [29]. The duration and amplitude of these motion profiles can be adjusted to match individual gait requirements. For superior rehabilitation performance and patients’ comfort, patient-specific reference trajectories are generated. For example, trajectories are obtained through the pelvic motion measuring system in WalkTrainer [67]. Subjects walk several times at slow, average and fast speeds. Each gait cycle is recorded and analysed to produce subject-specific trajectories [78]. An alternative approach is the “teaching” strategy of *Pneumatically Operated Gait Orthosis* (POGO) [96]. The robot essentially acts as a motion capture device, recording trajectories when the net actuator forces are zero. Subject-specific gait patterns are computed by identifying step cycles. The *Imitation learning system* [60] is also developed for generating trajectories. This system divides patient’s trajectories during different tasks into multiple motion segments and adapts the motion segments to patients’ movements and daily life environments.

*Complementary Limb Motion Estimation* (CLME) [97] is proposed to enable self-dominated gait for patients with severe unilateral impairment (e.g., resulting from stroke). The CLME uses statistical regression equations to extract couplings between limbs in healthy synergetic motion.

Reference trajectories can also be generated from dynamic parameters such as velocities [67], interaction forces [91, 98] or movement frequencies. In another approach, adaptive oscillators of a periodic input signal are used to estimate the patient’s movement while performing a task involving cyclical motion [99, 100].

### 2.2.2 Robot-in-charge control strategies

The *robot-in-charge control strategies* (RIC) are usually implemented in the initial stage of the rehabilitation process. The RIC strategies guide the patient to follow a
predefined motion, torque, force or impedance pattern [53-56]. This modality requires the robot to have relatively high joint impedance [101].

Most RIC strategies have high intrinsic stiffness. The trajectories of the robots are controlled by high gain feedback controllers [102], which allow for little, if any, reference trajectory deviation. There are other types of controllers employed in RIC strategies. For example, the robust controller of SUBAR [54] is able to deliver desired torque with low impedance. The impedance force controller of RiceWrist [55] is able to deliver desired impedance.

However, this type of control is no longer recommended for gait rehabilitation during chronic phase because of the intrinsic need for safety and compliance in the physical human-robot interaction [57].

2.2.3 Patient-robot cooperative control strategies

Position control with a fixed reference movement pattern, one of the RIC strategies, has been proven to be as effective as manual therapy for severely affected patients [31, 37]. However, new results indicate that therapy is more successful if the patient can participate actively [29, 36]. Evaluations of diverse rehabilitation methods such as constraint induced movement therapy [98], functional electrical therapy [103], or assist-as-needed therapy (AAN), confirm this finding [34]. Thus, patient-robot cooperative control strategies (PRC), governed by which patients can participate actively during gait training [29], are promising and primary control strategies in robotic gait rehabilitation.

The term patient-robot cooperation means three factors [29]. Firstly, the robots must be compliant and allow deviations from the predefined movement trajectory. It must be flexible and gentle in reaction to patient’s own muscular effort. Secondly, adaptation is needed to deal with movement deviations and the different voluntary
level of the patients. Thirdly, interaction must be taken into account because there are bi-directional energy and information exchanges between robot and patient.

The PRC control strategy is based on recognition of the patient’s voluntary efforts using sensors to directly or indirectly detect information such as joint moments [29], interaction forces [104], reaction torques [105, 106], surface EMG signals [107], joint angular velocities [107], interaction stiffness [99] or frequencies [100].

There are three basic approaches to realize PRC strategies.

*The first approach is to tolerate deviations from a given fixed reference trajectory by using a compliant device [61, 108] or a compliant controller [29].*

For gait rehabilitation robots equipped with compliant actuators, *sliding mode controllers* (SMC) are considered to be the most suitable position controllers [91]. The SMC allows deviations from reference trajectories. It is also capable of achieving both tracking accuracy and safety. However, SMC is based on the unrealistic assumption that there are no time delays in the feedback loop. When SMC is directly implemented in a real system with a discrete-time controller, repetition of delayed switching on the sliding surface causes high-frequency oscillation (i.e. chattering [109]).

Two modified SMC controllers are developed to deal with the chattering problem. One solution is the *proxy-based sliding mode control* (PSMC) [53, 102, 109], by which the combination of accurate trajectory tracking and safe response to perturbations can be achieved. The PSMC can also achieve smooth, over-damped recovery from a large positional error after abnormal events [109]. The PSMC controller is used by KNEXO [53], a unilateral exoskeleton with a knee joint powered by PPAMs, and it provides the system with a controlled compliance allowing deviations in both space and gait timing. In [102], PSMC controller guides
robotic manipulators to follow a subject’s movement, placing a tool at a predetermined position or along a predefined trajectory.

The other modified sliding mode control is the *boundary layer augmented sliding mode position controller* (BASMC). The BASMC is applied to control the position and compliance of PMA separately to meet acceptable safety criteria [91].

Another strategy that allows both spatial and temporal deviation is *path control* [110], which tolerates joint motions within a virtual “tunnel”.

*The second approach is to use trajectory adaptation algorithms to adapt the patient’s movement, muscular effort, or voluntary level.*

Using cycle-to-cycle adaptation methods can minimize interaction torques [68]. An *automatic position reference trajectory adaptation principle* is applied to any adaptive reference based control strategy, such as position or impedance control, to overcome the limitations of individual adjustment reference trajectories [29]. This method adapts trajectory parameters by online optimization and modifies the robot motion as desired by the patient [68, 111, 112]. A *fuzzy-logic based controller* applied in a MONIMAD prototype [113] adapts the trajectory by the patient’s or nurse’s personal choice.

One pneumatic assistive robot [61] synchronizes a reference pattern constantly with the patient’s gait. Two impedance controllers (force based impedance controller and position based impedance controller) are applied to control Lokomat [29]. Impedance control [114-117] is a kind of robust approach to regulate dynamic behaviour at the point of interaction. This aims to maintain a prescribed relationship between force and motion of the robot. The impedance of these two impedance controllers is time-varying and allows flexibilities in variable deviations from a
given leg trajectory. The leg trajectory depends on the patient’s efforts and the behaviours on the impedance parameters chosen by the patient or therapist.

The admittance torque control of NEUROExos provides the patient with an assistive torque with near-zero output impedance. This closed-loop control architecture is a classical PID regulator, with a saturation interval for the speed of the hydraulic piston and an anti-wind-up scheme [101]. A new adaptive admittance control law using the results of a real-time interaction stiffness estimation has been designed to match more adequately human cooperative motions [99].

The teach-and-reply algorithm of the POGO [118] is designed to manipulate both pelvis and legs during gait training [61]. The algorithm is based on the principle that no or minimum assistance should be given by trainers so long as the patient is able to sustain stable stepping motion by himself, but more assistance is provided “as needed” if the stepping pattern begins to degrade or collapse. The teach-and-reply algorithm provides assist as needed assistance by comparing states (position and velocity) of the individual with the desired states (reference patterns). It then accelerates or decelerates the timing of the replayed pattern.

The WalkTrainer [56] uses muscle stimulation based on EMG measurements. Forces that the users apply to the orthosis are minimized via the continuously updated muscle stimulation to enable the patient follow predefined walking patterns.

The third approach is to abandon the constraints of a fixed reference trajectory.

A gravity-compensating assistance strategy [119] relieves the patient from the need to support their body weight, even though it doesn’t introduce any power. Guidance of limbs is offered by Virtual Mode Control, which has been implemented on the LOPES [60, 78, 120].
These three strategies rely on voluntary, sufficiently coordinated activity in the impaired limbs. *Severely affected patients* have little influence on the reference trajectory so that they are led along a fixed pattern, which reduces to the RIC strategy.

**Biological cooperation based strategies**

The biological cooperation or feedback helps to figure out the patient’s contribution in real-time. The biological information provides necessary feedback and training instructions. The most popular *biological cooperation methodologies* are *visual cooperation, surface EMG cooperation, ground reaction force and hybrid biological cooperation* of these methodologies.

Some control strategies use visual feedback to patients and the therapists. The patients are motivated to improve his/her gait pattern during the therapy. The therapists can evaluate the patient’s effort, provide instructions to the patient, and assess the therapeutic progress [29]. For instance, Lokomat employs a visual biofeedback by a graphical presentation of patient’s performance related to the patient’s activity including hip and knee joint angles and the interaction forces. At the end of each stance or swing phase, one set of data is ready to be displayed in order to provide biofeedback to the patient.

Some robotic devices include sEMG signals in their control systems. sEMG signals are often used to estimate motion intention as the onset of sEMG signals precede actual human movements by approximately 30 ms-130 ms [121]. An exoskeleton equipped with sEMG is able to compensate the inherent time delay of a human-machine cooperation system. The sEMG signals recorded from selected muscles are used as indicators of efforts generation to trigger assistance. EMG-based controllers are successfully used to reduce the metabolic cost of walking assistance [122], or to
provide full-body daily assistance [89]. Artificial neural networks are employed to approximate the nonlinear relationship between sEMG and limb motions, without detailed human limb biomechanics [121]. However, sEMG recordings suffer from some drawbacks related to signal stability [123], which lead to the need for periodic recalibration and may also cause discomfort to the user in long periods of time (e.g., skin irritation).

### 2.2.4 Challenge-based control strategies

Unlike RIC strategies or PRC strategies, challenge-based strategies make a task more difficult or challenging. However, these control strategies are more properly viewed as a continuum along which task difficulty is varied to challenge the participant optimally [71].

Examples include controllers that provide *resistance* to the participant’s limb movements during exercise, require specific patterns of force generation or increase the size of movement errors (*error amplification strategies*).

**Resistive strategies**

The therapeutic strategy of providing resistance to the participant’s hemiparetic limb movements during exercise has a long history in clinical rehabilitation. For example, the *proprioceptive neurofacilitation therapy* technique advocates resisting participants’ motions along *diagonal movement patterns* during rehabilitation training [124]. There is a reasonable amount of evidence showing that this type of therapy can indeed help post-stroke patients to improve motor function [125-127].

There are a few attempts to use resistive training in robotic therapy. Examples of resistive robotic devices that apply constant resistive forces to the affected limb, independent of its position or velocity, are proposed for reaching and grasping practice [128-131] or for walking [132, 133]. Many of these robotic devices use
resistance based training as one of the multiple therapy options of the robotic device, usually for participants with low-level impairment. A more sophisticated resistance technique [134] involves the application of a viscous resistance (i.e. a resistive force in the direction of movement proportional in magnitude to the affected limb’s velocity). Given that gravity always exists, moving against gravity can be considered as a variant of the resistive approach. Cancelling gravity only as needed has been proposed with several robotic devices that can actively generate a counterbalance force through the robot’s control system [135-138]. These devices have the ability to partially compensate for weight of the limb and robot, increase the resistance on the participant’s limb and demand a higher effort from the impaired limb.

**Error-amplification strategies**

RIC or PRC strategies reduce movement errors from predefined movement tasks. However, research on motor adaptation has emphasized that kinematic errors generated during movement are a fundamental neural signal that drives motor adaptation [139-141]. Thus, researchers propose robotic therapy algorithms that amplify movement errors rather than decrease them. Riesman et al. [140] described studies which amplified curvature errors during reaching by persons with chronic stroke. The robotic force field caused participants to move straighter, at least temporarily, when the force field was removed, compared to reducing curvature errors during training. Researchers also explore the effect of increasing limb phasing error in patients’ post-stroke gait through a split-belt treadmill, thus increasing walking spatial-temporal asymmetries during a short adaptation session. The adaptation induced temporary after-effects causing walking symmetry in participants who had shown asymmetries at the baseline stage. Related work in this area shows that unimpaired subjects are able to adapt more quickly by transiently amplifying their movement errors for the task of learning to walk in a robotic force field [139].
2.2.5 Compliant actuator controller

The actuation system executes control commands passed from high-level controller and middle-level controller via the actuator controller (see Figure 1.3). The need for compliant actuators is increasing along with the growing demand for closely interacted gait rehabilitation robots. In order to provide safe and effective interaction behaviour, compliant controllers, other than the traditional PID controllers, are introduced. These include modified PID control [142], adaptive control [143-145], controllers based on the computed torque method [146, 147], neural networks [148, 149], sliding mode control (both simulation studies [150, 151] and implementation [143, 152]) and other nonlinear control methods [150, 153], as well as the recently introduced equilibrium point control method [154]. Table 2.2 summarizes several compliant actuator controllers.
### Table 2.2: Compliant actuators controller

<table>
<thead>
<tr>
<th>Controller</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impedance control [114-116]</td>
<td>Regulate both force and motion, Robust, soft and compliant</td>
<td>Unstable at high impedance, Not feasible to direct specify the desired assistive force</td>
</tr>
<tr>
<td>Admittance control [155-157]</td>
<td>Better stability at higher impedance</td>
<td>Lacks of classical tools in the accurate and simultaneous analysis of the effect of control parameters on both stability and performance</td>
</tr>
<tr>
<td>Sliding mode control [143, 150-152]</td>
<td>Deal with modelling uncertainty by applying additional terms to a nominal model</td>
<td>Discontinuous across the sliding surface $s=0$, chattering</td>
</tr>
<tr>
<td>Gait phase-based smoothed sliding model control [91]</td>
<td>Apply the saturation function instead of the signum function based on the gait phase</td>
<td>The chattering phenomenon and tracking performance can be trade off</td>
</tr>
<tr>
<td>Proxy-based sliding mode control [109]</td>
<td>Good tracking performance, Safe response to large deviations from the target position, Improved safety</td>
<td>NA</td>
</tr>
</tbody>
</table>

*Literature Review*
2.3 Neuromusculoskeletal models for improving the effectiveness of the gait rehabilitation

Gait rehabilitation robots interact with human, both physically and cognitively. Thus the entire system can be considered as a human-robot system. Moreover, design of human-robot system and control strategy design can be improved by incorporating human’s intention, patient-specific musculoskeletal system and also the biomechanical principle of human locomotion.

Based on the discussion of abovementioned control strategies, in order to improve the effectiveness of the rehabilitation robot, the patient’s musculoskeletal model as well as anthropometric and anatomy information is needed for accurate modelling. Exploiting the biomechanical principles of human locomotion is used for obtaining the patient-specific gait reference trajectory. Taking into account human’s intention is used for improving the human-robot interaction.

2.3.1 Musculoskeletal model

The state-of-the-art musculoskeletal models used to obtain muscle-tendon properties, muscle-tendon kinematics, muscle-tendon dynamics, the anatomical parameters and anthropometric parameters of body segments, are normally subject-specific interactive graphic-based geometrical models [81, 158]. They are usually scaled from generic models by employing musculoskeletal modelling and simulation tools [1]. The generic model defines the bone surfaces of pelvis, femur, patella, tibia, fibula and foot. The model also defines the joint kinematics of the lower limbs and the musculotendon paths of those muscles of lower limbs. The bone surfaces provided by SIMM, OpenSim [1, 81], or Anybody [159] are usually obtained by digitizing a male skeleton with known anthropometric dimensions. The musculotendon paths of those selected muscles are modelled as a series of points
connected by line segments. The musculotendon paths also include muscle origin and insertion points as well as additional intermediate points, which are defined when the muscle wrapped over the joint surface. The patient-specific musculoskeletal model is scaled from the generic model based on patient’s anatomical position. The accurate anatomical information of each subject is usually obtained through a 3D motion capture system such as VICON (Oxford Metrics Group, Oxford, UK). Figure 2.2 shows an example of musculoskeletal modelling using OpenSim 2.4.0.

Figure 2.2: A demo of musculoskeletal modelling using OpenSim 2.4.0. The subject is scaled from the generic musculoskeletal model 3DGaitModel2392 based on markers’ positions recorded maintaining a static pose [2].
2.3.2 Gait analysis and assessment techniques

Gait analysis techniques provide quantitative information about human gait. The main parameters obtained from gait analysis are:

- Temporal-spatial parameters such as cadence, step length, stride length, or ratio of stride length to lower extremity length [160-165],
- Stride parameters such as foot contact pattern, stride time, stance phase (%), single leg support (%), step time [161-163], and joint range of motion (ROM) [163, 164],
- Gait kinematics such as angles (relative and absolute), angular velocity and angular accelerations [164, 166-168],
- Gait kinetics such as force, moment, and power [167-169],
- EMG patterns [161, 162].

Based on these parameters, various scales have been developed to give an overall measure of walking capability for patients with stroke and other neurological defects. These include the gait abnormal rating scale [163], the Rivermead Mobility Index [170] and the Rivermead Visual Gait Assessment.

Among all of the five measurement systems, three focus on the specific events that constitute the act of walking. Motion analysis defines the magnitude and timing of individual joint action. Dynamic electromyography identifies the period and relative intensity of muscle activation. Force plate displays the functional demands being experienced during the weight-bearing period. Each of these systems serves as a diagnostic technique for one facet of gait. The two remaining gait analysis techniques summarize the effects of the person’s gait mechanics. To determine
overall walking capability, one measures the patient’s stride characteristics, while efficiency is revealed by energy cost measurements [8].

Accelerometers [166], video cameras [163, 171] or 3D motion analysis systems [169] are used to gather data for offline gait analysis. Some devices are also developed for gait assessment based on kinetics and kinematic data of the specific patient. For instance, an instrumented shoe is developed for pathological gait assessment based on the instantaneous vertical forces and plantar pressures exerted during gait [172].

Standard gait analysis techniques serve as important diagnostic tools to inform better rehabilitation robot design. Researchers use inverse dynamics analysis to design exoskeletons, which mimic normal human joint kinematic and kinetic patterns [72]. Potential changes in the distribution of joint torques and powers across the ankle, knee, and hip due to rehabilitation robot loading can be assessed by comparing joint dynamics during locomotion with and without actuation of the robot [80].

2.3.3 Muscle force estimation via optimization algorithms

Understanding forces applied to a joint and estimating how these forces are distributed among surrounding muscles, ligaments, and articular surfaces are fundamental to understand the joint function, injury, and disease. Inverse dynamics can be used to calculate the external load applied to a joint. However, given the indeterminate nature of the joint, the contribution from muscles to support or generate this load is far more difficult to determine.

Individual muscle forces during walking give in-depth information on neural control and tissue loading of gait. The individual muscle forces thus contribute to improve the diagnosis and management of neurological or orthopaedic conditions. Direct
measurement of individual muscle forces is difficult. Minimal invasive measurements only estimate muscle forces in superficial tendons such as the Achilles [173, 174]. Direct measurements of muscle forces can also be achieved by placing force transducers on tendons during surgery [175-178]. On the whole, non-invasive methods based on a musculoskeletal model are needed. However, estimation of individual muscle forces in vivo is a challenging task because human musculoskeletal system is a highly redundant system.

One solution of solving the redundancy problem is to estimate muscle forces based on optimization algorithms. Static optimization [179-185] and dynamic optimization [186-189] are two main methods. Redundant muscular force sharing is solved by minimizing objective functions within an optimization routine (e.g., minimizing muscle stress, muscle forces or muscle activations).

### 2.3.3.1 Static optimization

There are many studies employing static optimization algorithms to study individual muscle forces in the lower limbs during walking. Seireg and Arvikar [180] predicted muscle forces of 31 muscle groups and seven segments from lower extremities, based on minimization of the weighted sum of muscle forces and the moments at all joints. The resultant muscle forces are consistent with typical electromyogram patterns of level walking from the literature. Crowninshield et al. [181, 185] estimated muscle forces of 27 and 47 muscle groups around hip, knee and ankle joints by minimizing sum of different power of muscle stresses. They also tested the sensitivity of the power of the objective function and found that three was the most appropriate. They also find that muscle force patterns are not sensitive to small changes of objective function power.

Patriarco et al. [183] estimated muscle forces of 31 muscle groups of the lower limbs by minimizing the sum of muscle forces and also the mechanical-chemical power.
They find that incomplete information on the physiological function and individual muscles cause large errors for accurate determination of muscle forces. Rohrle et al. [182] predicted individual muscle forces for 42 muscle groups and six degrees of freedoms by minimizing the sum of muscle forces. The sensitivity of muscle origin/insertion points to muscle forces and joint forces were analysed. The results show that muscle origin/insertion points are more sensitive to joint forces.

Brand et al. [190] investigated the sensitivity of physiologic cross-sectional area to muscle force by using a musculoskeletal model consisting 47 muscle groups around three joints. Other research groups also investigate the influences of different objective functions on muscle force prediction. Collins [191] calculated muscle forces from seven muscle groups around three joints by minimizing the sum of muscle forces (or squared), muscle stresses, ligament forces, contact forces and instantaneous muscle power. Results show that minimization of total ligament force cannot successfully predict muscle activation when compared with EMG signals. Glitsch and Baumann [179] compared the muscle force prediction performance of 47 muscle groups around three joints when using different objective functions such as minimizing the sum of muscle forces, muscle force squared, muscle stresses, muscle stresses squared and muscle stress cubed. Results demonstrate that minimizing the sum of muscle stresses squared combined with less constrained joints predict the best performance.

Some studies focus on muscle force prediction of knee joint flexion/extension using static optimization. Dul et al. [192] compared the characteristics and performance of different objective functions for static-isometric knee flexion. The results show that linear objective functions predict discrete muscle activation, while nonlinear objective functions predict more realistic muscle activation. Li et al. [193] also tested the effectiveness of using different objective functions to predict muscle forces from
ten muscle groups during isometric knee flexion and extension. The experiments show that all three objective functions (linear, nonlinear and physiological) can predict antagonistic muscle forces. The performance of muscle force prediction is more sensitive to kinematic information than to objective function. Forster et al. [194] studied co-contraction of antagonistic muscles and predicted and controlled co-contraction for the knee joint model.

The inverse dynamics-based static optimization method is able to calculate joint moments and individual muscle forces using kinematic data and ground reaction force information. However, it is limited in the following aspects:

- Firstly, it is highly sensitive to body segmental kinematics [183, 188]. The kinematics should be as accurate as possible.
- Secondly, it is difficult to model muscle coordination [63]. Therefore, the applications of static optimization algorithm are limited to movements with minimal co-contraction such as normal gait [195].
- Thirdly, current static optimization models cannot realize real-time calculation. Current models use at least “several minutes” to predict muscle forces from ten or more muscle groups during knee flexion and extension [193].

2.3.3.2 Dynamic optimization

Dynamic optimization is not subject to the limitations of static optimization and can ideally produce more realistic muscle forces. Dave and Audu [188] solved muscle forces sharing problems using dynamic optimization by minimizing tracking error and metabolic energy consumption. The method was validated using a typical static optimization algorithm and the EMG signal values taken from literature. Yamaguchi and Zajac [196] performed normal gait simulation by including ten muscle groups and eight degrees of freedom of the lower limb. The objective function minimized
tracking error and the sum of cubed muscle stress. Neptune et al. [189] examined individual muscle contributions of ankle plantar flexors to actuate body segments including support and forward progression and swing initiation.

Dynamic optimization is not sensitive to kinematics data and can accurately represent the underlying physiological properties of the system. However, the multiple integrations make the algorithm computationally expensive. Therefore, it is not convenient to be used in clinical or even real-time applications. Previous studies show that static optimization and dynamic optimization can yield similar accuracy for muscle forces for human gait [195]. Applications need to be computationally efficient can consider static optimization, which estimates individual muscle forces \textit{in vivo} and at the same time takes into account of physiological properties.

Despite the undoubted success of both static optimization and dynamic optimization, they have been focused on offline analysis and have not been applied to provide biological control command for the \textit{human-inspired rehabilitation robots}. Evidently, inverse-dynamics static optimization inherently has the potential to realize real-time muscle force estimation because it does not require multiple integrations [195].

\textbf{2.3.4 Muscle force estimation via EMG-driven models}

Another approach to estimating muscle forces \textit{in vivo} uses \textit{electromyography} (EMG) in conjunction with appropriate musculoskeletal and muscle mechanics model to estimate forces. Since \textit{EMG-driven models} rely on measured muscle activity to estimate muscle force, they implicitly account for a subject’s individual activation patterns without the need to satisfy any constraints imposed by objective functions.

The EMG signals provide an indirect indicator of muscular function. The electric signals, which accompany the chemical stimulation of the muscle fibres, travel through the muscle and adjacent soft tissues. With appropriate instrumentation, these
myoelectric signals can be recorded and analysed to determine timing and relative intensity of the muscular effort. In some circumstances, one can also estimate the resulting muscle forces [89]. Also, EMG information is one of the best indicators of muscle activity for patients with neurological lesions, which impair voluntary control such as the spastic disabilities of cerebral palsy, stroke, brain injury or spinal cord injury [8, 197, 198].

The EMG data experimentally recorded from the major muscle groups are used to drive multiple musculotendon units (MTUs) within a subject-specific physiologically accurate model of the human musculoskeletal system. In this scenario, the recorded EMG signals directly determine the patterns of MTU excitations and the resulting MTU forces and moments. This approach has the advantage, over optimization-driven methods, of solving the neuromuscular redundancy problem based on an individual’s estimate of the neural drive without having to make assumptions on how MTUs share the load about a joint.

2.3.4.1 Anatomical based EMG-driven models

Anatomical based EMG-driven models are based on Zajac’s [199] musculotendon actuator model, the classical Hill-type model, and the anatomical musculoskeletal models [199-203]. Previous EMG-driven models of varying complexity have been used to estimate kinetics (such as the individual muscle forces and joint moment [204-212]) and joint kinematics (such as the joint angle, velocity, and accelerations [158, 206, 207]). Those models are able to work on lower limb joints such as hip joint [211], knee joint [204, 206, 211], or ankle joint [205, 206, 208-211]. Such EMG-driven models include three main parts: the anatomical musculoskeletal model providing musculotendon length and muscle moment arms for selected muscles, the activation dynamics model converting raw EMG signals to muscle activations, and
the muscle contraction dynamics converting the muscle activation to muscle forces [158, 199, 204-213].

The EMG-driven models are mainly built upon anatomical musculoskeletal models [81, 214-217]. Bogey, Perry and Gitter [208] developed an EMG-driven ankle model based on one generic musculoskeletal geometric model. Musculotendon parameters such as the maximum muscle isometric force, optimal muscle fibre length, muscle pennation angle, or musculotendon length are adopted from anatomical studies [214-216]. They have good agreement with the ankle moment calculated by inverse dynamics. One reason is that the participants are average size adult males who closely match the generic anatomical musculoskeletal model. This model cannot account for individual variations and is likely to give less good agreement for other subjects. More and more models are employing the patient-specific musculoskeletal model to account for individual variability and a subject’s own anatomical properties [158, 204, 206-210]. These patient-specific musculoskeletal models are based on computer-interactive 3D musculoskeletal models and then scaled to the subjects using anatomical landmarks [158, 209].

Digital signal processing and activation dynamics involves the processing of raw EMG signals to estimate muscle excitations and then muscle activations, which form the inputs to EMG-driven models. Amplification, band-pass, high-pass or low pass filtering, full-wave rectification, linear envelop processing, and moving average are main processing steps used to convert the raw EMG signals to muscle excitations [158, 204, 206-211].

The EMG-driven models include muscle activation dynamics and muscle contraction dynamics to predict muscle fiber forces from raw EMG signals. These models use first-order nonlinear differential equations [205], second-order differential equations [204, 207-210], or activation state converter [158] to deal with muscle
activation dynamics. Muscle contraction dynamics deals with the conversion of muscle activations to individual muscle forces. It normally consists of two parallel units: the \textit{contractile element} (CE) and the \textit{passive element} (PE) \cite{199, 204-206, 208}. Some models include a \textit{series elastic element} (SEE) \cite{158} to represent the \textit{non-linear elastic component} and the \textit{viscous component} (see Figure 2.3). The contraction dynamics are modelled as separate \textit{force-length} (FL) and \textit{force-velocity} (FV) relationships \cite{158, 204, 206-210} or a \textit{combined force-length-velocity} (FLV) relationship \cite{205}.

The total muscle force $F^m$ is the sum of passive force $F^{PE}$ and active force $F^{CE}$. Structures putatively responsible for these forces are called the \textit{passive element} (PE) and the \textit{contractile element} (CE). Force $F^{CE}$ depends on muscle fiber length $L^m$, velocity $V^m$, and the state of activation of the muscle fibers $a(t)$. Force $F^{PE}$ depends on muscle fiber length $L^m$.

$$F^m = F^{CE} + F^{PE} \quad (1.4)$$

$$F^{CE} = F(L^m, V^m, a(t)) \quad (1.5)$$

\textbf{Figure 2.3:} Hill-type model for contraction dynamics of muscle tissue.
\[ F^{PE} = F(L^n) \] (1.6)

Most anatomical based EMG-driven models predict joint moments and individual muscle forces with an acceptable accuracy for a single degree of freedom (DOF). For example, using one DOF EMG-driven models, Bogey et al. [208], Thelen [205] and Shao et al. [210] modelled ankle dorsiflexion and plantar flexion, Lloyd and Besier [204] modelled knee flexion and extension, and Manual et al. [207], Koo and Mark [158] modelled elbow flexion and extension. Among these one-DOF EMG-driven models, some estimate the joint moment and muscle forces across a variety of tasks in order to be robust when the models are implemented in multi-tasks. Lloyd and Besier [204] performed maximum isometric contractions for flexors and extensors, eccentric hamstring and quadriceps contraction, low effort flexion/extension, combined flexion/extension from the dynamometer tasks, and a series of running trials (including a straight run, sidestep and a crossover cut). Koo and Mak [158] estimated elbow joint angle and elbow muscle forces during three flexion/extension tasks: loaded voluntary elbow flexion, unloaded voluntary elbow flexion and unloaded voluntary elbow extension. The results show that the EMG-driven model is task dependent. The EMG-driven models need to be re-calibrated carefully when working on a different task.

Multi-DOF EMG-driven models are developed to generate a more realistic representation of muscle activation patterns, muscle forces or joint moments during a number of dynamics tasks. Sartori, Reggiani, Lloyd and Pagello [211, 212] developed a multi-DOF EMG-driven model using EMG signals recorded from 16 muscles driving 34 musculotendon actuators in nine dynamic tasks (e.g., walking, running, sidestepping and crossover, hip adduction-abduction, hip flexion-extension, hip internal-external rotation, knee flexion-extension, ankle dorsiplantar flexion and ankle subtalar movement). The results show that the model generated muscle forces
satisfying all DOF simultaneously. The model also has great potential to predict more physiologically accurate muscle forces than those predicted by previous single DOF EMG-driven models.

Some EMG-driven models can be modified for older patients [205] or patients with neurological disorders [210]. Thelen [205] used adjusted parameters (muscle deactivation time constant, isometric strength, maximum contraction velocity, maximum normalized force, and passive muscle strain due to maximum isometric force) to account for changes in muscle properties with aging. Shao et al. [210] developed an EMG-driven model to estimate the muscle forces and joint moment of the ankle joint for stroke patients. Instead of adjusting the musculotendon mechanical parameters in FLV relationship and tendon strain-length relationship [210], they modified four muscle activation dynamics parameters and four parameters of muscle contraction dynamics (e.g., optimal muscle fibre length, tendon slack length, the global percentage change in optimal muscle fibre length and the maximum isometric force). The modification takes into account of altered muscle activation and movement patterns for stroke patients.

2.3.4.2 Non-anatomical based EMG-driven models

Not all EMG-driven models are based on anatomical musculoskeletal models. Pau et al. [218, 219] developed a one DOF EMG-driven model for estimating elbow flexion and extension angle. This model was based on a simplified geometric model, which treated the elbow joint as a single hinge with a fixed centre of rotation to the joint angle, actuated by two main muscle groups. The muscle moment arms and musculotendon lengths are calculated using trigonometry. Pau’s model also simplified the musculotendon model by including only muscle fibres. Although they predicted elbow joint angle with acceptable performance, the simplifications on the musculoskeletal model and the musculotendon model make it difficult to adapt this
model to the lower limb. Ding et al. [220] developed an *EMG-driven state space model* for the elbow joint with only one muscle actuator. This model did not include musculoskeletal, anatomical or geometric details. The EMG-driven state space model combined the hill-type model with joint forward dynamics, which mapped muscle activations to the joint motion. Two EMG features, the *integral of absolute value* and *waveform length*, were used to estimate elbow joint velocities and angle via the *Extended Kalman Filter*.

**2.3.4.3 EMG-driven models designed for robotic application**

There is an increasing interest in employing EMG-driven models in gait rehabilitation robots. For instance, Song et al. [221] developed real-time EMG-driven arm wrestling robots to estimate individual muscle forces via EMG signals. They used *wavelet packet transformation* and an *autoregressive model* to extract EMG characteristics. An *artificial neural network* was used to map the EMG signal to elbow joint force. Ryn et al. [222] developed an EMG-driven controller to replicate the wrist movement by estimating the wrist joint angle via EMG signals. The model obtained “quasi-tension” by performing signal processing. A supervised multi-layer neural network trained by a back-propagation algorithm was used to estimate wrist angle. They claimed that their model improved the effectiveness of the teleoperated robotic manipulator.

In some cases, modifications are made to existing anatomical based EMG-driven models for real-time robotic applications. Sartori et al. [223] made a set of enhancements [204] in order to reduce the time and memory requirements and to provide real-time operation for controlling a lower limb powered orthosis. They designed a more efficient algorithm, which allowed integration of all sub-models into a single framework and reduced the demand for memory to achieve real-time calculation. Firstly, they replaced the elastic tendon of the Hill-type muscle model
with a stiff tendon. Secondly, they created three different 2D tables per muscle to store subject-specific musculotendon length values calculated via SIMM. At each run, the tables were indexed based on the current joint positions.

Some EMG-driven models are integrated with virtual reality technology to give bio-feedback for those who are limbless or born with congenital defects or required rehabilitation. Patients are familiarized with their new limb and movement ability and intention in the Virtual Training Environment. Al-Jumaily and Olivares [224] developed an EMG-driven below-shoulder 3D human arm integrated with virtual reality. Their model was based on signal classification and anatomical structure with virtual reality modelling. Sartori et al. [225] developed a 3D virtual model of the lower limb for potential use of a real-time EMG-driven gait rehabilitation exoskeleton. They developed a graphical interface, which allowed the user to visualize the skeletal geometry and the movement driving it.

2.3.4.4 Effectiveness and limitation of the current EMG-driven models

The effectiveness of the EMG-driven model is normally represented by the joint kinetics prediction performance [204, 206-209] (e.g., joint moment prediction or individual muscle force), or joint kinematics prediction performance [218-220, 226] (e.g., joint angle, joint velocity, or joint acceleration).

Joint moment prediction performance is calculated by comparing the moment calculated via the EMG-driven model and that calculated via inverse dynamics. 3D motion capture systems [204, 206, 208, 209] or sensors [206-209, 219] can both be used for inverse dynamics calculation and for recording joint moment, joint angle or muscle forces. The values obtained are used as references. The coefficient of determination $R^2$ is normally used to represent the prediction performance between the joint moment or angle predicted by the EMG-driven model and the references.
EMG-driven models can predict joint kinetics or joint kinematics with good performance. For instance, Bogey et al. [208] predicted ankle joint moment with an average $R^2$ value of 0.97 in comparison with the inverse dynamics moment. Buchanan et al. [206, 209] and Lloyd et al. [204] predicted knee and ankle joint moments with $R^2$ value of 0.91 and 0.94, respectively. The peak Achilles tendon force predicted, 2900 N, is similar with the recorded tendon force using a transducer (2600 N).

EMG-driven models are limitation on several aspects:

- Firstly, a large part muscle mechanics models treat the FL and FV relationship separately [204, 209, 212, 219]. However, it is not physiologically to use the FL and FV relationships separately [227, 228].

- Secondly, the non-anatomical based EMG-driven models are not based on specific subject. The models are either based on simplified geometric models [218, 219] or even not include musculoskeletal, anatomical or geometric details [220]. These models are difficult to take into account patients’ variability and musculotendon properties.

- Thirdly, EMG-driven models based on classification-type approaches can only work on movements that they have been trained and cannot deal with novel movements [218, 219].

- Fourthly, the current iterative algorithms such as the Runge-Kutta-Fehlberg algorithm cannot realize in real-time [229].

- Fifthly, previous EMG-driven models tend to include as many muscles as possible [208] around each joint with a large number of adjustable parameters to ensure good prediction. This leads to a longer calculation time or a poor prediction ability for novel data [206].
Table 2.3: Anatomical based EMG-driven models


<table>
<thead>
<tr>
<th>Model</th>
<th>Goal</th>
<th>DOF</th>
<th>Muscles</th>
<th>Musculoskeletal model</th>
<th>Signal processing</th>
<th>Muscle activation dynamics</th>
<th>Muscle contraction dynamics</th>
<th>Amount of optimization parameters</th>
<th>Optimization algorithm</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Begey et al [208]</td>
<td>AF and AM</td>
<td>P/D</td>
<td>A: 7</td>
<td>Generic anatomical model [214-216]</td>
<td>Normalization, Rectification, Integration</td>
<td>Filter</td>
<td>FL, FV</td>
<td>NA</td>
<td>SAA</td>
<td>$R^2$ 0.97,</td>
</tr>
<tr>
<td>Buchanan et al.</td>
<td>EM, KM and AM</td>
<td>E: 7, K: 10, A: 4</td>
<td>Geometric model [217]</td>
<td>Filter, rectification, normalization</td>
<td>Differential equation</td>
<td>FL, FV</td>
<td>4 for each muscle, 4 in activation dynamics; 2 global gain factors</td>
<td>SAA</td>
<td>$R^2$ 0.91(K) and 0.94 (A)</td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>Goal</td>
<td>DOF</td>
<td>Muscles</td>
<td>Musculoskeletal model</td>
<td>Signal processing</td>
<td>Muscle activation dynamics</td>
<td>Muscle contraction dynamics</td>
<td>Amount of optimization parameters</td>
<td>Optimization algorithm</td>
<td>Evaluation</td>
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<tr>
<td>Lloyd et al. [204]</td>
<td>KM</td>
<td>KFlex/Ext</td>
<td>K: 13</td>
<td>Anatomical model</td>
<td>Rectification, filter</td>
<td>Discrete non-linear model</td>
<td>FL, FV</td>
<td>15 MT parameters and 3 muscle activation parameters</td>
<td>Non-linear least squares algorithm</td>
<td>$R^2 0.91$</td>
</tr>
<tr>
<td>Manual et al. [207]</td>
<td>EM, EF</td>
<td>E: 7</td>
<td>Anatomical model</td>
<td>Rectification, filter, linear envelop</td>
<td>Differential equation</td>
<td>FL, FV</td>
<td>5 EMG-to-activation coefficients</td>
<td>Non-linear optimization</td>
<td>Calculation less than 40 ms</td>
<td></td>
</tr>
<tr>
<td>Thelen [205]</td>
<td>AM</td>
<td>AP/D</td>
<td>A: 4</td>
<td>Anatomical model</td>
<td>NA</td>
<td>Differential equation</td>
<td>FLV</td>
<td>6 MT parameters</td>
<td>NA</td>
<td>Better prediction</td>
</tr>
</tbody>
</table>
Table 2.3: Anatomical based EMG-driven models (continued)

<table>
<thead>
<tr>
<th>Model</th>
<th>Goal</th>
<th>DOF</th>
<th>Muscles</th>
<th>Musculoskeletal model</th>
<th>Signal processing</th>
<th>Muscle activation dynamics</th>
<th>Muscle contraction dynamics</th>
<th>Optimization parameters</th>
<th>Optimization algorithm</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Koo et al. [158]</td>
<td>AF and Am</td>
<td>E: 7</td>
<td>GoM</td>
<td>Geometrical model</td>
<td>Filter, rectification, normalization.</td>
<td>EMG-activation state converter</td>
<td>FL, FV [213]</td>
<td>3 MT parameters per muscle</td>
<td>Optimization</td>
<td>Successful prediction</td>
</tr>
<tr>
<td>Shao et al</td>
<td>AF and AM</td>
<td>A: 4</td>
<td>Am</td>
<td>Anatomical model</td>
<td>Amplification, Filter, Rectification, Linear envelop</td>
<td>Differential equation</td>
<td>FL, FV</td>
<td>4 activation dynamics parameters, 4 MT parameters.</td>
<td>Stochastic optimization</td>
<td>$R^2$ between 0.87 and 0.92</td>
</tr>
<tr>
<td>Model</td>
<td>Goal</td>
<td>DOF</td>
<td>Muscles</td>
<td>Musculoskeletal model</td>
<td>Signal processing</td>
<td>Muscle activation dynamics</td>
<td>Muscle contraction dynamics</td>
<td>Amount of optimization parameters</td>
<td>Optimization algorithm</td>
<td>Evaluation</td>
</tr>
<tr>
<td>-------------</td>
<td>----------</td>
<td>-----</td>
<td>--------------------</td>
<td>-----------------------</td>
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<td>---------------------------</td>
<td>-----------------------------</td>
<td>----------------------------------</td>
<td>-----------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Sartori et al. [211, 212]</td>
<td>HF, HM, KF, KM, AF, AM</td>
<td>H: 16</td>
<td>HAdd/Abd, HFlex/Ext, KFlex/Ext, AP/D</td>
<td>Geometric model [217]</td>
<td>Rectification, filter, normalization</td>
<td>Differential equation</td>
<td>FL, FV</td>
<td>4 in activation dynamics, 2 global gain factors</td>
<td>SAA</td>
<td>More physiological accurate</td>
</tr>
<tr>
<td>Pau et al. [218, 219]</td>
<td>Em</td>
<td>E: 2</td>
<td>EFlex/Ext</td>
<td>Simplified geometric model</td>
<td>Linear envelop</td>
<td>NA</td>
<td>FL, FV</td>
<td>2 addition scale factors</td>
<td>Generic algorithm</td>
<td>Average RMSE of 6.53 degree</td>
</tr>
<tr>
<td>Ding et al. [220, 226]</td>
<td>Ev and Em</td>
<td>E: 1</td>
<td>EFlex/Ext</td>
<td>NA</td>
<td>Feature extraction</td>
<td>NA</td>
<td>state-space model, EKF</td>
<td>5</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>
2.4. Summary

This literature review summarized previous research and highlighted limitations on control strategies of gait rehabilitation robots and neuromusculoskeletal models.

This chapter firstly reviewed four control strategies of gait rehabilitation robots, which are robot-in-charge control (RIC), patient-robot-cooperative control (PRC), patient-in-charge control (PIC), and challenge-based control. The closely physical human-robot interaction gives rise to more requirements to the control strategies for improving the effectiveness of the gait rehabilitation robot. The robot should be safe, comfortable and take into account human’s intention.

Among these four control strategies, the review shows that the most developed and accepted one is the PRC strategies. Current PRC strategies employ the following methods to fulfill the aforementioned requirements and to improve the effectiveness of gait rehabilitation.

- Firstly, the interaction torque or force between the robot and the patient is minimized through accurate dynamic modeling. Thus patients walk comfortably during gait training [72].

- Secondly, through the adaptation and deviation of the predefined trajectory of gait training, the so-called “assist-as-needed” or compliance is achieved [29, 53, 61, 157, 230].

- Thirdly, patients’ voluntary efforts are encouraged through interaction, kinetic, kinematic or biological information from patients [53-56].

Despite of the success of current control strategies, this review also identifies the following two research gaps on how to deliver optimal gait training.

- Firstly, current control strategies cannot effectively take into account patient’s variability. Instead of obtained from the patient-specific
musculoskeletal system, the anthropometric, geometry or anatomical parameters for modeling human-robot systems are either from existing databases [74] or measured from one subject [75].

- Secondly, current PRC strategies detect patients’ efforts based on kinematic and kinetic information [53-56]. Such control strategies cannot include patients’ voluntary movement or active muscle effort [79]. The strategies limit the potential of gait rehabilitation robots because they cannot introduce more physiological inputs to the central nerve system, which lead to better rehabilitation [79].

Neuromusculoskeletal models have the potential to improve the effectiveness of gait rehabilitation robots by modelling patient’s dynamics more accurately and detecting the patient’s intention. The review shows that the subject-specific musculoskeletal models [81, 158] provide accurate anatomical or anthropometric parameters of segments. The models can also provide patient-specific muscle parameters (such as musculotendon parameters) or musculotendon kinematics [231]. These parameters could be used to model patient’s dynamics accurately. Individual muscle forces, regarded as patient’s intention or active muscle effort, can be estimated in vivo by static optimization algorithms [179-185] or EMG-driven models [204-212].

However, these models cannot be directly used to control gait rehabilitation robots. The common limitations are:

- Some models are either based on simplified geometric models [224, 225] or even not include musculoskeletal, anatomical or geometric details [226].
- Most current neuromusculoskeletal models cannot realize real-time calculation. Current models uses at least “several minutes” to predict muscle forces from ten or more muscle groups during knee flexion and extension [193, 229].
For EMG-driven models, a large part of the muscle mechanics models treat FL and FV relationship separately, which is not physiologically meaningful.

For employing the neuromusculoskeletal models in gait rehabilitation robots, the models need to be improved by realizing real-time calculation and ensuring accurate muscle force prediction.
Patient-specific muscle force estimation model for swing-assist gait rehabilitation

Individual muscle forces during movement *in vivo* could be viewed as motor intention. *Static optimization* has been used to calculate joint torque individual muscle forces using *musculoskeletal models*. In this chapter, a novel muscle force estimation model for robotic application is presented.
3.1 Introduction

*Gait dysfunctions* are common outcomes of neurological injury and disease [232]. It is showed that *swing phase assistance*, either by therapists or by robotic devices, has positive outcomes. *Swing phase training* improves walking speeds, endurance, and performance on functional tasks for individuals with acute and chronic spinal cord injuries [22, 233-238].

Gait rehabilitation robots, which are precise, are tireless, and can even quantitatively assess rehabilitation effectiveness with high accuracy [39], yield better training outcomes than traditional manual therapies conducted by physiotherapists. One of the state-of-the-art gait rehabilitation robots is *human-inspired gait rehabilitation robot* [53, 99, 239]. The *human-inspired gait rehabilitation robots* are inspired by patient's *musculoskeletal system* and mimic the antagonistic actuators around joints in order to produce intrinsically compliant behaviours to work in harmony with patients. The *human-inspired robotic exoskeleton (HuREx)* [239] developed in *Mechatronics Lab of the University of Auckland* is the test bed in this thesis.

A number of rehabilitation control strategies have been developed for such robots. These controllers are normally based on kinematic information (such as angular position and velocity), kinetic information (such as interaction forces and moments) or impedance patterns [53-56] from the position sensors and force sensors of the robots.

According to the neuromuscular control theory of gait [23] and the clinical evidence, an optimal control strategy should comprise task-specificity [51], repeatability, intensity and optimal physical and mental engagement [52]. Current up-to-date control strategies are limited in the following two aspects:

- Firstly, the existing controllers fail to fulfil the requirement of optimal
biological engagement and self-initiative both in system modelling and in controller design. These controllers are normally based on kinematic information (such as angular position and velocity), kinetic information (such as interaction forces and moments) or impedance patterns [53-56] from the position sensors and force sensors of the robots. These controllers are suboptimal because they do not take into account the patient’s own voluntary movement and the mechanism of neuromuscular control [34, 46].

- Secondly, dynamic modelling of the patient and controlling the human-robot interaction are not accurate for current gait rehabilitation robotic controllers. To the best knowledge of the author, there are no controllers based on the musculoskeletal model of the specific patient. For example, the anthropometric parameters are based on approximations from experiments or simplified to constitute a linear relationship for the consideration of real-time calculation [240, 241]. These controllers represent the variable properties of a specific subject and cannot represent subjects’ variability.

Thus, an optimal controller for a human-inspired gait rehabilitation robot, which ensures optimal neurological rehabilitation effectiveness and safety, should be based on physiological properties, specific subject, and patient’s own voluntary movement and intention.

Techniques in biomechanics such as three-dimensional (3D) musculoskeletal modelling, gait analysis techniques and muscle force estimation techniques can be used in controllers of human-inspired gait rehabilitation robots to model the human dynamics more accurately and detect the patient’s intention. A possible solution is controlling the robot by desired muscle forces based on the patient-specific musculoskeletal model. Estimation of individual muscle forces in vivo is a challenging task because human musculoskeletal system is a highly redundant system. Static optimization [179-185] and dynamic optimization [186-189] are two
main methods of solving the redundancy problem. Redundant muscular force sharing is solved by minimizing objective functions within an optimization routine (e.g., minimizing muscle stress, muscle forces or muscle activations). Previous studies show that static optimization and dynamic optimization can yield similar accuracy for muscle forces for human gait [195]. Applications requiring computationally efficient can consider static optimization. Static optimization does not require multiple integrations [195], estimates individual muscle forces in vivo and at the same time takes into account of physiological properties.

Figure 3.1: The structure of the patient-specific biological command-based controller. The single degree of freedom limb joint actuated by two antagonistically hill-type muscle actuators is from reference [3].

The purpose of this research is to develop a patient-specific muscle force estimation model (PMFE) for the potential use of the human-inspired robotic exoskeleton. The general idea is demonstrated in Figure 3.1. The patient-specific musculoskeletal model is established and scaled to represent a specific patient in the first place [2]. The patient’s anthropometric and anatomical parameters derived from the musculoskeletal model are used in the robot’s mechanical structure and controller design. Desired extensor and flexor muscle forces during swing phase calculated via the PMFE serve as the control inputs of the antagonistic actuation system. Detail of
the PMFE is described in section 3.2. Combined with the kinematics and ground reaction forces, gait properties can be analysed offline in order to enable the robot following patient’s own gait trajectory.

To improve the accuracy of muscle force prediction and realize patient-specific modelling, the patient-specific musculoskeletal model is employed in the PMFE to obtain accurate anatomical parameters and muscle moment arms. To realize real-time calculation, an analytical algorithm, the *Lagrange multiplier method* (LMM), is implemented in the static optimization procedure. The musculoskeletal model is also simplified according to patient's muscular mechanism (anthropometric parameters and activation of muscles) and the actuation system of the rehabilitation robot. The *computed muscle control* (CMC) method [81, 242, 243] is introduced to evaluate the PMFE by comparing muscle forces and joint moment calculated via the PMFE and the CMC using the same kinematic data. The activation durations of surface electromyogram (sEMG) signals from the same muscles are chosen to evaluate the PMFE further by comparing the muscle activation with the muscle force estimated by the PMFE.

### 3.2 Patient-specific muscle force estimation

The PMFE (see Figure 3.2), which is the PMFE block in Figure 3.1, is a patient-specific inverse dynamics static optimization model. The PMFE is built on a computer-generated two-dimensional musculoskeletal model, which provides anthropometric, anatomical parameters and muscle kinematics (moment arms) of each segment OpenSim [1, 2]. The patient-specific musculoskeletal model is scaled based on the computer-generated musculoskeletal model according to the anatomical positions recorded in a static trial [81]. Joint moments are calculated from the kinematic data for each joint, musculoskeletal parameters and external forces via inverse dynamics [186]. Note that the external forces are not included in the PMFE
during swing phase. Muscle forces are then estimated via a static optimization technique based on joint moments and muscle moment arms. As demonstrated in Figure 3.2, the PMFE includes online and offline calculation. For each subject, the patient-specific musculoskeletal modelling is carried out offline. Once the muscle parameters and muscle moment arms are obtained for one subject, the same values will be used in the following training trials for the specific subject.

![Image of the patient-specific muscle force estimation model (PMFE)](image)

Figure 3.2: The structure of the patient-specific muscle force estimation model (PMFE). The PMFE includes three models: patient-specific musculoskeletal model, inverse dynamics and static optimization.

### 3.2.1 Patient-specific musculoskeletal model

The patient-specific musculoskeletal model of the PMFE [1] (see Figure 3.3) consists of femur and tibia representing thigh and shank, treated as rigid bodies with revolute joints, which move only in the sagittal plane. The pelvis is fixed in the model. The muscle group *iliopsoas* and *gluteus* represent hip flexor and extensor. The (quadriceps) *rectus femoris* (RF) and *biceps femoris* (BF) represent knee extensor and flexor. Each rigid body is characterized by mass, length, moment of inertia about the center of mass and distance from the center of mass to the proximal joint.

The musculoskeletal model is built on a generic 3D musculoskeletal model in *OpenSim* [81, 158] and then scaled down [81, 244] according to the anthropometric
data of the subject and kinematic data from the gait analysis experiment. This simplification is based on human musculoskeletal function during walking and most importantly according to the actuator arrangement of the human-inspired robotic exoskeleton (HuREx) [239], which uses two antagonistic artificial muscles and cables to mimic the human musculoskeletal system. Only the hip and knee flexion and extension in sagittal plane during swing phase are included in the PMFE. Furthermore, the ankle joint and foot operate mainly during the stance phase and thus are viewed as a mass point at the end of the tibia [5] in the swing phase.

Figure 3.3: The patient-specific musculoskeletal model of the PMFE. Hip joint and knee joint, and four muscles (one flexor muscle and one extensor muscle around each joint) are included in this model. The model is scaled to specific subject.
### 3.2.2 Inverse dynamic modelling

Figure 3.4: The link-segment system of lower limb. Red lines are global coordination system \((x_0, y_0)\). Green lines are hip joint local coordination system \((x_1, y_1)\). Blues lines are knee joint local coordination system \((x_2, y_2)\).

Net joint moments are calculated using inverse dynamics based on joint kinematics, segment parameters and external forces (3.1).

\[
\begin{bmatrix}
    M_{11} & M_{12} \\
    M_{13} & M_{14}
\end{bmatrix}
\begin{bmatrix}
    \dot{\theta}_1 \\
    \dot{\theta}_2
\end{bmatrix}
+ \begin{bmatrix}
    C_{11} & C_{12} \\
    C_{13} & C_{14}
\end{bmatrix}
\begin{bmatrix}
    \theta_1 \\
    \theta_2
\end{bmatrix}
+ \begin{bmatrix}
    g_1 \\
    g_2
\end{bmatrix}
+ E = \begin{bmatrix}
    \tau_1 \\
    \tau_2
\end{bmatrix} \tag{3.1}
\]

Where \(\theta = [\theta_1, \theta_2]^T\) is the two joint angles (hip and knee respectively), \(\tau = [\tau_1, \tau_2]^T\) is the joint torques, \(M\) \(\begin{bmatrix}
    M_{11} & M_{12} \\
    M_{13} & M_{14}
\end{bmatrix}\) is the human-robot system mass matrix, \(C\) \(\begin{bmatrix}
    C_{11} & C_{12} \\
    C_{13} & C_{14}
\end{bmatrix}\) is the centrifugal and coriolis loading, \(G\) \(\begin{bmatrix}
    g_1 \\
    g_2
\end{bmatrix}\) is the gravity and \(E\) represents the external force (which is not include in this period because of swing phase are only considered). Note that for the human-robot system, \(M\), \(C\) and \(G\) models both the patient and the robot. \(M\), \(C\) and \(G\) are explained by segment mass \(m\), segment length \(l\), the proximal segment length from center of mass \(l_c\) and joint angles \(\theta\).
The details are as follows:

\[ M_{11} = l_1 + l_2 + m_1 \cdot l_{c1}^2 + m_2 \cdot l_{c2}^2 + 2m_2 \cdot l_1 \cdot \cos \theta_2, \]

\[ M_{12} = M_{21} = l_2 + m_2 \cdot l_{c2}^2 + m_2 \cdot l_c \cdot l_1 \cdot \cos \theta_2, \]

\[ M_{22} = l_2 + m_2 \cdot l_{c2}^2, \]

\[ c = m_2 \cdot l_{c2} \cdot l_1 \cdot \sin \theta_2, \]

\[ C_{11} = -2 \cdot c \cdot \dot{\theta}_2, \quad C_{12} = -c \cdot \dot{\theta}_2, \quad C_{21} = -c \cdot \dot{\theta}_1, \quad C_{22} = 0, \]

\[ g_1 = (m_1 \cdot l_{c2} + m_2 \cdot l_1) \cdot g \cdot \cos \theta_1 + m_2 \cdot l_{c2} \cos (\theta_1 + \theta_2), \]

\[ g_2 = m_2 \cdot l_{c2} \cdot g \cdot \cos (\theta_1 + \theta_2). \]

The external force is not included. Because the PMFE is highly sensitive to the accuracy of the raw kinematic data, angular accelerations are calculated via the second derivative of the digitally filtered coordinated data, which showed better performance in comparison with accelerometer and finite difference [245].

### 3.2.3 Moment arms of muscles

The patient-specific muscle moment arms are produced by OpenSim [1], which models the musculotendon paths wrapping around points and/or surfaces [2, 81]. It is desirable that moment arms are continuous to ensure good muscle force prediction. However, the obstacle detection [246] algorithm causes discontinuities in the predicted moment arms [246, 247]. To this end, third-order Fourier equations combined with the obstacle detection are developed in this study to represent muscle moment arms for one entire swing phase. Figure 3.5 shows the muscle moment arms of a typical subject. Table 3.1 shows parameters of the Fourier equations.
Figure 3.5: Muscle moment arms from hip flexor, hip extensor, knee flexor and knee extensor. Moment arms during swing phase are normalized to 100 frames.

The Fourier equations are as follows:

$$y = a0 + \sum_{i=1}^{3}(a_i \cdot \cos(iwx) + b_i \cdot \sin(iwx)),$$  \hspace{1cm} (3.3)

where $y$ is the moment arm, $x$ is normalized swing phase framework (0-100), $a_i$, $b_i$ and $w$ are Fourier parameters (see Table 3.1). The coefficient of determination ($R^2$) represents the fitting performance between moment arms before and after Fourier fitting. Figure 3.5 and Table 3.1 show that the moment arms are continuous and have good prediction performance ($R^2 > 0.9$). Once the parameters of equation (3.2) are defined for each subject, the equation is used for representing the subject’s time-variable moment arms.

<table>
<thead>
<tr>
<th></th>
<th>HF</th>
<th>HE</th>
<th>KF</th>
<th>KE</th>
</tr>
</thead>
<tbody>
<tr>
<td>a₀</td>
<td>0.037</td>
<td>0.032</td>
<td>0.026</td>
<td>0.038</td>
</tr>
<tr>
<td>a₁</td>
<td>0.0059</td>
<td>-0.0028</td>
<td>-0.00048</td>
<td>-0.0019</td>
</tr>
<tr>
<td>b₁</td>
<td>-0.0029</td>
<td>0.0021</td>
<td>-0.0019</td>
<td>-0.0032</td>
</tr>
<tr>
<td>a₂</td>
<td>0.00073</td>
<td>2.4e-05</td>
<td>0.0010</td>
<td>0.00092</td>
</tr>
<tr>
<td>b₂</td>
<td>-0.00086</td>
<td>0.0013</td>
<td>-0.00027</td>
<td>-0.0013</td>
</tr>
<tr>
<td>a₃</td>
<td>-0.00075</td>
<td>0.00029</td>
<td>-0.00011</td>
<td>1.8e-05</td>
</tr>
<tr>
<td>b₃</td>
<td>0.00094</td>
<td>-0.00024</td>
<td>-0.00025</td>
<td>0.00030</td>
</tr>
<tr>
<td>w</td>
<td>0.036</td>
<td>0.032</td>
<td>0.060</td>
<td>0.046</td>
</tr>
<tr>
<td>R²</td>
<td>0.99</td>
<td>1</td>
<td>0.98</td>
<td>0.99</td>
</tr>
</tbody>
</table>

### 3.2.4 Static optimization

Static optimization has been widely used to estimate muscle forces in vivo during gait [180, 183, 248, 249]. It is an extension to inverse dynamics that further resolves the net joint moment into individual muscle forces at each instant in time. The muscle forces are resolved by minimizing an objective function. The objective function used in this study is based on the sum of forces cube. It is based on the fact that the energy conservation of normal gait is optimal [5]. Muscle forces are constrained to maximum isometric forces and the equilibrium joint moment equations. Maximum isometric forces are obtained through the patient-specific musculoskeletal model discussed in section 3.2.1. Corresponding joint moment equilibrium equation is formulated for each joint.
\[ G = \min \sum_{i=1}^{m} q_i \cdot F_i^n \]  

Subject to:

\[ \sum_{i=1}^{m} R_i \cdot F_i = M_{ext} \text{ and } 0 \leq F_i \leq F_{\text{maxi}} \]  

\( G \) is the objective function. \( m \) is the number of muscles selected for each joint. \( q_i \) represents the weight factor of design variables. \( F_i \) is the calculated muscle forces. Note that in static optimization, \( F_i \) is scalar. At each instant time, the direction of skeletal muscle force is always known. It is along the muscle fibres and pulls the bones it is attached to [5]. \( n \) is the power of the objective function, let \( n=3 \), \( R_i \) is the moment arms of chosen muscles around each joint, \( M_{ext} \) is the total external moment, and \( F_{\text{maxi}} \) is the maximum muscle forces. The weight parameters \( q_i \) are sensitive to the resultant joint moment and muscle forces. Therefore, they are optimized by the genetic optimization algorithm, in which the objective function is the root mean square error (RMSE) between the experimental joint moments and the estimated joint moments. Once the weight parameters are defined for one subject, it is used to estimate joint moments and muscle forces of other subjects and trials.

In order to realize real-time calculation, the objective function is minimized via the LMM equation (3.6), which is an analytical algorithm. The muscle forces and Lagrange multiplier can be calculated through the partial differential equation (3.4).

\[ L(F_i, \lambda) = \sum_{i=1}^{m} q_i \cdot F_i^n - \lambda (\sum_{i=1}^{m} R_i \cdot F_i - M_{ext}) \]  

### 3.3 Evaluation and results

Gait analysis data from six healthy adolescents (age: 12.9±3.81 years; leg length: 0.81±0.093 m; weight: 52.62±20.05 Kg) [250] at their self-selected speeds (1.09±0.08 m/s) are used to evaluate the PMFE. The experimental data include the
markers’ position data, ground reaction forces and the sEMG. Model scaling and inverse kinematics are applied to obtain the joint angles.

### 3.3.1 The PMFE evaluation

The usual way to validate the muscle forces is to compare them with those calculated by other methods [251, 252] or with the respective sEMG signals [195]. CMC is a popular approach to provide realistic estimations of muscle forces [81, 239, 242, 243]. To evaluate the PMFE, muscle forces calculated via the PMFE and CMC are compared using the same joint kinematics data, anatomical parameters, and muscle moment arms. In addition, the sEMG signals from hip/knee flexors/extensors are introduced to evaluate the PMFE because sEMG is the indicator of the muscle activation level [8].

There are more muscles at each joint in the CMC than the PMFE when comparing the two models. Two muscles act as the hip extensor and flexor respectively in the PMFE. In contrast, 13 muscles act as hip extensors and twelve muscles act as hip flexors in the CMC. For the knee joint, two muscles work as knee extensor and flexor, respectively; four muscles act as knee extensors and eight muscles act as knee flexors in the CMC despite muscle co-activation of hip and knee joints [81]. In order to make muscle forces from these two methods comparable, a way to combine muscle forces of extensors and flexors in the CMC into one extensor and one flexor at each joint is needed.

The *muscle force combination algorithm* (3.7) developed for muscle forces via the CMC is based on individual muscle functions. The algorithm also guarantees that the combined virtual extensor and flexor of each joint generate the same moment with that individual muscles (original, before combination) can generate. The combined
virtual hip and knee flexors and extensors have the same moment arms as the PMFE method for better comparison.

\[
F_{com} = \sum_i p_i \cdot F^i \cdot C_r \cdot C_{sig}, \quad (3.7)
\]

\[
C_r = \frac{R(q)_i}{R(q)_{PMFE}} \quad (3.8)
\]

where \( i \) is the number of muscles contributing to hip (or knee) extension (or flexion), \( F_{com} \) is the combined muscle forces of the virtual joint extensor (or flexor) from all extensors (or flexors) investigated in the CMC, \( F^i \) is individual muscle forces, \( C_r \) is the coefficient related to moment arms (3.7) of the \( i_{th} \) muscle, \( C_{sig} \) is the coefficient related to muscle activation and contribution to hip (or knee) extension (or flexion) during swing phase (3.6) [5, 253], \( R(q)_i \) represents the \( i_{th} \) individual extension (or flexion) muscle of hip (or knee) joint, \( R(q)_{PMFE} \) is the respective moment arm of hip (or knee) extensor (or flexor) and \( p_i \) is the scaling factor (0-1), which is obtained via an optimization algorithm to ensure the combined CMC muscle force can generate same joint moment using OpenSim inverse dynamic tools.

### 3.3.3 Simulation results

Muscle forces calculated by the PMFE and the CMC [81, 242, 243] are compared. The Coefficient of determination \( (R^2) \) and the average root mean square error (RMSE) between the muscle forces via the PMFE and the CMC are calculated. \( R^2 \) and the RMSE are also implemented on the net joint flexion/extension moment predicted by the PMFE and OpenSim inverse dynamic (ID) pipeline as the sum effect of muscle forces.

\( R^2 \) is called coefficient of determination in statistics [271] and is calculated by (3.9)

It gives information about the goodness of fit of a model. In other words, the \( R^2 \) is a statistical measure of how well the prediction results approximates the real data.
ranges from 0 to 1. An $R^2$ of 0 means that the simulation results cannot fit actual value at all. An $R^2$ of 1 means that the prediction perfectly fit the real data.

$$R^2 = \frac{SSR}{SST} \quad (3.9)$$

Here $SSR$ is the sum of squared regression and $SST$ is the sum of square total.

Hip joint flexion moment via the PMFE is smaller than that via the ID pipeline of OpenSim at the initial and final stage of swing phase and larger at the middle of swing phase ($RMSE = 0.04 Nm/Kg$) (see Figure 3.7 and Table 3.2). The shapes of the two hip flexion moments’ time series are similar ($R^2 > 0.95$). The $R^2$ and $RMSE$ are demonstrated in Table 3.2.
Figure 3.6: The knee and hip flexion/extension moments calculated via PMFE in comparison with those from the ID tool of OpenSim during swing phase. Moments are mean values of the six subjects and are normalized by body weight (Nm/kg). Hip flexion and knee extension moments are positive, while hip extension and knee flexion moments are negative. Note that the red curves are joint moments calculated by ID tool and the blue curves are those calculated by the PMFE. The shaded curves are the minimum and maximum joint moments.
Table 3.2: Comparison of hip and knee joint moment calculated by the PMFE and the Inverse Dynamics pipeline of OpenSim

<table>
<thead>
<tr>
<th></th>
<th>Hip moments</th>
<th>Knee moments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PMFE</td>
<td>OpenSim</td>
</tr>
<tr>
<td>Min</td>
<td>-0.4577</td>
<td>-0.4572</td>
</tr>
<tr>
<td>Max</td>
<td>0.4061</td>
<td>0.4205</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9787</td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>0.04</td>
<td></td>
</tr>
</tbody>
</table>

Muscle forces calculated from the PMFE and the CMC are similar in time series shapes and magnitudes (see Table 3.3). All muscle forces from the two methods have good correlations ($R^2 > 0.8$ for all cases). Peak values of muscle forces calculated from both the PMFE and the CMC are all similar (see Table 3.3) and the averaged RMSE is in a reasonable range.
Table 3.3: The knee and hip flexor and extensor forces from the PMFE and the CMC during the swing phase are compared. Muscle forces are mean values of the six subjects and are normalized by each subject’s body weight (N/kg). The peak values and standard deviations, $R^2$ and the RMSE between the averaged muscle forces calculated via PMFE and CMC are shown.

<table>
<thead>
<tr>
<th></th>
<th>Hip flexor</th>
<th>Hip extensor</th>
<th>Knee flexor</th>
<th>Knee extensor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PMFE</td>
<td>OpenSim</td>
<td>PMFE</td>
<td>OpenSim</td>
</tr>
<tr>
<td>Min</td>
<td>1.2</td>
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<td>0.83</td>
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<tr>
<td>Max</td>
<td>8.5</td>
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</tr>
<tr>
<td>$R^2$</td>
<td>0.92</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>0.90</td>
<td>0.76</td>
<td></td>
<td></td>
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</tbody>
</table>

The activation durations of hip/knee flexors and extensors are compared with the muscle forces estimated by the PMFE as an additional indirect evaluation (see Figure 3.7). As demonstrated in Figure 3.7, the activation durations of knee flexor muscle and knee extensor muscle are similar to those calculated by the PMFE.
Figure 3.7: Absolute muscle forces normalized to body weight from knee flexor and knee extensor VS. sEMG activation durations from hip/knee flexor/extensor muscles. Red and blue curves are the averaged joint flexor forces and extensor forces respectively. The shaded areas represent the minimum and maximum muscle forces. The bottom thick black lines are the muscle activation durations.

The computational efficiency of the PMFE is evident in comparison with the CMC because of the simplified musculoskeletal model and the analytical computational algorithm. To calculate muscle forces during swing phase (mean swing phase time span is 0.45s), the PMFE takes a very short time (mean computational time is 0.02s), which has great potential in terms of realizing real time.
3.4 Discussion

The PMFE aims to calculate muscle forces actuating joints for specific patients in real-time. The application in gait rehabilitation robots leads to two requirements for the PMFE: real-time computation and accurate representation of muscle forces. To realize real-time computation, the musculoskeletal model implemented in PMFE is simplified to two joints and four muscles. Furthermore, an analytical algorithm, LMM, is utilized in the optimization process of the PMFE. To increase the computation accuracy, the PMFE introduced the two-dimensional musculoskeletal computer-generated model which is customized firstly to the subject offline to get the "accurate" anatomical parameters, anthropometric parameter and the "accurate" moment arms of muscles.

The proposed PMFE model has been proved to be a promising method to provide accurate muscle forces as the biological control inputs for rehabilitation robots. Joint moment (see Figure 3.6 and Table 3.2) and the corresponding extensor and flexor muscle forces (see Figure 3.7 and Table 3.3) calculated by the PMFE was compared with those calculated via Inverse Dynamics (ID) tool of OpenSim and computed muscle control (CMC) algorithm. ID and CMC are well-defined approaches to provide realistic estimations of joint moment and muscle forces [81, 186, 231, 239, 242, 243, 245, 252, 254]. Therefore, the hip and knee joint moments calculated via the ID tool of OpenSim and the muscle forces calculated via the CMC tool of OpenSim are regarded as the “ground truth” or “actual value” of the corresponding hip and knee joint moments and muscle forces. The results showed that the PMFE model estimated joint moment and individual muscle forces accurately. The $R^2$ values between hip and knee flexion/extension moment calculated via the PMFE and the ID tool of OpenSim were greater than 0.95 and the averaged RMSE values were 0.04 Nm and 0.022 Nm respectively. Muscle forces calculated via the PMFE and the
CMC had good correlations. The averaged R² values of knee/hip extensor and flexor muscle forces were 0.89. The joint moments and muscle forces predicted by the PMFE were similar to those reported in the literature [5, 181, 183, 195]. Similar to other static optimization models [183, 185, 193, 195], muscle force patterns predicted via the PMFE model were agreeable with muscle activation levels (reflected by EMG signals). Normally it took more than 200 seconds to calculate joint moments and individual muscle forces using ID and CMC tools of OpenSim from kinematics data from one gait cycle [231]. The PMFE, compared with those OpenSim tools, showed great computational efficiency with the mean calculation time is 0.02 ± 0.003 s for the entire gait swing phase (about 40% of gait cycle).

Although muscle force estimation involves multiple steps, only the first step, the patient-specific musculoskeletal modelling, takes extra time to determine the subject-specific parameters, which is used as the input of the model. In addition, the offline musculoskeletal modelling does not need to be done for every training session as those anatomical parameters are constant values for each person. All other steps have been integrated as one computer program and can be completed in real time.

In this research, only swing phase is considered because of the following two reasons. Firstly, for patients with neurological disorders leading to gait deviations, swing phase deviations are related to quadriceps spasticity, hip flexion weakness, ankle dorsiflexion weakness or spasticity, hamstring contracture, hamstring spasticity and quadriceps weakness, which lead to inadequate knee joint flexion and extension as well as excessive knee joint flexion and extension. These problems have similar effects on gait stance phase, which indicate training on swing phase may have positive effects on the entire gait cycle [8, 23]. There are already some swing-assist robots developed [255, 256] and show positive rehabilitation training outcome.
Secondly, the application is limited to swing-phase because of the hardware design of the current HuREx. The HuREx does not integrate hardware, which can record ground reaction forces (GRF) in real-time. Therefore, the inverse dynamics model of the PMFE cannot estimate joint moment and then individual muscle forces during the stance phase of gait.

There are two main methods to incorporate GRF in real-time in order to expand the PMFE to the entire gait cycle. Firstly, the GRF can be estimated based on kinematics [257], pressure insoles [258-263] or directly measure the ground reaction forces by force plates. Secondly, it is also plausible to estimate the GRF based only on joint kinematics [259, 264] using equations for inverse dynamics of human motion [264]. The GRF estimation performance can be improved by combining forward dynamics [265] or optimization techniques [266].

It is important to discuss the assumptions of the musculoskeletal model of the PMFE. Movements during swing phase are in the sagittal plane and the torso is assumed to be immobile during the entire swing phase. The joints are considered to be hinge joints and only the flexion and extension of each joint are considered. A foot is considered as a mass point at the proximal point of the tibia. This is a significant simplification for the lower extremity. Gait is complicated and needs the cooperation of hip, knee, and ankle joint with the monarticular and biarticular agonists or antagonists at each joint. Hip abduction/adduction, medial/lateral rotation, and knee pronation/supination all help to generate gait movement. The reasons for these assumptions are that swing phase only is investigated and flexion/extension at hip and knee joints is most important in gait swing. What is more, the rehabilitation robot is swing-assist and only works for hip and knee flexion and extension. We admit that all these assumptions affect the accuracy of muscle force estimation to some degree. The muscle force estimation results of the PMFE show, however, that
these assumptions are acceptable and are a good trade-off between the estimation performance and computational efficiency.

The patient-specific musculoskeletal model is the foundation of muscle force estimation and is all-important. The musculoskeletal models using computer-generated images of musculoskeletal structures determine more accurate muscular-tendon paths for all the major lower extremity actuators and change these paths efficiently according to joint angles. The musculoskeletal geometry and actuator force-generating properties of the model in this study were tested previously [81, 243] to ensure that they adequately represent normal human anatomy and physiology. The scaled musculoskeletal model is regarded as the patient-specific musculoskeletal model [81].

The accuracy of each muscle’s moment arm in its respective joint has a huge influence on the accuracy of muscle force estimation [253]. Measuring the time-variable moment arm of an individual muscle during movement is challenging. Tendon travel in specimen studies [267], computed tomography [268] or magnetic resonance imaging [81] are the main methods used to determine the moment arms of muscles. However, the tendon travel method cannot be measured in vivo for ethical reasons. Even though the muscle moment arm as a function of angle is able to be derived from tendon travel experiments on human cadavers [267], it is an average approximation, rather than subject-specific. Although magnetic resonance imaging from a specific patient provides more accurate moment arms, it introduces processing complexity and consequently needs a large amount of time. Previous studies [181, 251] used average constant value as the moment arm of each muscle and therefore introduced large errors to muscle forces estimated through optimization techniques. The muscle analysis pipeline of OpenSim combined with a
Fourier equation-fitting algorithm is a better solution for identifying muscle moment arms.

Key issues related to the PMFE need to be stated. Firstly, the *Hill-type muscle model* [201] is prevalent in the muscle modelling area. Through the *force-length* and *force-velocity* relationships as well as the *muscle activation level*, the magnitude of muscle forces can be obtained. However, research shows that for normal gait at low speed, the results of muscle forces are similar with or without Hill-type modelling [253]. In order to shorten the computation time of the PMFE further, muscle activation dynamics and *force-length-velocity properties* are not included. Second, objective functions of the static optimization are usually decisive factors in whether the force estimations are reasonable or not. Minimizing the sum of muscle squared (or cubed) or minimizing the sum of muscle stress squared (or cubed) are widely used algorithms in previous literature [181, 187]. The objective function used in this study is based on minimizing sum of muscle forces cubed because of the following reasons:

- Firstly, minimizing the sum of muscle forces cubed has been proved that has better muscle force prediction performance by previous research [195, 252, 269].

- Second, it is not feasible to minimize muscle stress in the objective function. The muscles investigated in the PMFE are virtual combinations of all muscles contributing to hip (or knee) flexion (or extension). It is difficult to define their physiological cross-sectional area.

- Thirdly, the human-inspired rehabilitation robot needs force information rather than stresses as control inputs.

Static optimization and dynamic optimization can provide similar estimations of muscle forces for human gait from the similar results from the PMFE (based on
static optimization) and the CMC (based on dynamic optimization). Anderson and colleagues [186, 195, 252] draw the same conclusion that static optimization rather than dynamic optimization is to be recommended if one only aims to estimate muscle forces and can also accurately calculate inverse dynamics. Joint moments illustrate the resultant actions of all muscles crossing a joint for the PMFE and the CMC (Figure 3.6). It is shown that forces calculated by these two methods can generate similar movements at hip and knee joint. Joint moments from the PMFE are also in agreement with those in the literature. This could further indicate that the assumptions and simplifications of the musculoskeletal model are reasonable during swing phase.

The PMFE is limited in the following aspects:

- Firstly, the PMFE does not consider the muscle co-activation effects, which influences the results of the static optimization algorithm used to solve the muscle redundancy problem. It is based on a simplified musculoskeletal model, which consists only of two muscles around each joint working as the joint extensor and flexor. However, the PMFE is developed to control a gait-swing assistant rehabilitation robot effectively. Walking at a low speed is a good activity to subject to the PMFE because muscle co-activation of opposing muscle groups is minimal [253]. It needs to be investigated and validated carefully if the PMFE is used in other activities.

- Secondly, this method can only be implemented in swing phase at this time, as the ground reaction forces are not taken into account. In the future, this robot can be expanded to assist and retrain the entire gait cycle. The ground reaction forces can be taken into account and the force platform to measure the ground reaction force can be synchronized with the robot.

- Thirdly, the evaluation of the PMFE is based on the assumption that the CMC method is a valid technique for muscle force estimation. Measured
experimental force data can be used for validation in the future.

The PMFE can be used to predict joint moment and muscle forces not only in lower limbs but also in upper limbs. For other control strategies such as a robot-human cooperative control strategy, the PMFE is able to provide predefined joint moment and muscle forces and also the muscle forces in vivo. To this end, in the area of rehabilitation robotic control, the PMFE will be a useful tool for understanding the status of joint flexors and extensors. Furthermore, we developed a patient-specific EMG-driven neuromuscular model to cover the patient’s abnormal status of muscle performance.

3.5 Summary

A patient-specific muscle force estimation model (PMFE) is proposed in this chapter. The PMFE is an anatomy-based inverse dynamic-static optimization model aiming to fulfill the requirements for controlling the human-inspired rehabilitation robot via muscle forces. It is targeted at providing real-time muscle force during gait. The PMFE is based on a two-dimensional computer-generated musculoskeletal model, which provides anatomical parameters and time-variable moment arms. The musculoskeletal model is simplified to consist of two segments and four muscles for the real-time computation requirement and controller design of a rehabilitation robot. An analytical optimization algorithm is also introduced to address the real-time requirement. This method has provided estimations of muscle forces that match well with those of the established CMC method from both experimental data [250] and literature. Combined with computational efficiency, the PMFE is a promising method to provide muscle forces as the biological control input for rehabilitation robots.
A patient-specific biological command based controller for human-inspired robotic exoskeleton

Muscle forces are able to be calculated via the patient-specific muscle force estimation model. These forces provide the gait rehabilitation robot the information of patients’ status and muscle functions. The next step is investigating how to employ the PMFE to control gait rehabilitation robots. This chapter proposes case study of employing the PMFE to control the human-inspired gait robotic exoskeleton. The focus is placed on how to translate patient’s status to robot status and pass the robot status to actuator controller.
4.1 Introduction

Preliminary studies find that individuals who receive the robotic task-oriented gait training demonstrate improved EMG activity during locomotion [44], walk more symmetrically [45], bear more weight on their legs [41], and experience higher returns in functional walking ability when compared with patients who receive conventional gait training [42]. Furthermore, evidence also shows that robotic training paradigms during rehabilitative training can be improved by more engagement of the patients with the utilization of patients’ own neuromuscular control [48-50]. It is important to develop effective robotic control algorithms that incorporate patients’ own neuromuscular system and movement intention. To this end, a patient-specific muscle force estimation model (PMFE) is proposed in Chapter 3 to estimate the patient’s muscle forces in vivo. In this chapter, a case study is reported on how to use these muscle forces to control gait rehabilitation robots.

To ensure optimal rehabilitation performance for the human-inspired rehabilitation robot, the patient-specific biological command based controller (PSBe) is proposed. The controller is based on the patient-specific musculoskeletal model and the PMFE model. The term biological command refers to desired individual muscle forces predicted by the PMFE model. The model is based on the patient-specific musculoskeletal system of the patient and provides individual muscle forces in vivo. Such muscle forces provide insight into neural control and tissue loading [186] and thus are considered as biological commands. The patient-specific musculoskeletal model provides the anatomical, anthropometric, and muscle kinematics for system modelling and controller design. The robotic actuators are a part of the human-robot system and are governed by the same biological behaviour with the patient, employing an optimization algorithm to map the muscle forces via the PMFE. A PMFE based feedforward controller, parallel with a feedback PID controller, works
as the lower level force controller of the two antagonistic \textit{pneumatic air muscle actuators} (PMA). The \textit{human-inspired robotic exoskeleton} (HuREx) \cite{239} is used to evaluate the PSBc. Kinematic data from six adolescents at three walking speeds and a sine wave were employed as the reference trajectories. Computer simulation and a robot experiment were performed to evaluate the position tracking and force tracking performance of the PSBc.

\section*{4.2 Methods}

\subsection*{4.2.1 Human-inspired Robotic Exoskeleton}

In this study, the HuREx \cite{239} is used as the test bed for the PSBc. Figure 4.1 demonstrates that the HuREx consists of two circuits, the pneumatic circuit and the electrical signal circuit, and one mechanical frame of the HuREx. The pneumatic circuit is the actuation system, including the pneumatic air compressor, pneumatic air muscles, filters, valves and so on. Two pneumatic air muscles at one joint work as the antagonistic actuators, while the Bowden cables connecting the PMAs to the exoskeleton are implemented as the tendons of the actuation system, mimicking human’s musculoskeletal systems to produce an intrinsically compliant and harmony behaviour. The muscle model is represented as a Hill-type muscle. The PMAs of HuREx are 40mm diameter with a length of 300mm from Festo (http://www.festo.com). They are selected according to the required joint torque and the pulley size. Steel Bowden cables with 2.5mm diameter transfer forces from the PMAs to the exoskeleton, with a similar function of tendons in the musculoskeletal system. The electrical signal circuit is the \textit{patient-specific biological command based controller} (PSBc), which is the main concern of our paper. The control system ensures that the PMAs generate desired muscle forces to actuate the exoskeleton, based on the pressure sensors and the position sensors, via the high-speed solenoid.
valves. The mechanical frames (e.g. thigh and shank attachment) of the robot are manufactured based on a 3D image of patient’s thigh and shank using a 3D printer.

Figure 4.1: The system schematic of the HuREx. The system includes a pneumatic circuit, an electrical signals circuit and the exoskeleton of the HuREx.

The control system designed of the robot was firstly developed in Matlab 2012 and then expanded to Labview 2012 and National Instrument CompactRIO 9072. Position sensors and pressure sensors are used for data acquisition in real-time to enable the robot to follow desired trajectory and forces.

### 4.2.2 Patient-specific biological command based controller

Figure 4.2: The concept of the patient-specific biological based controller
The PSBc aims to ensure that the robot follows the reference joint angles $\theta_d$ as well as the desired muscle forces from both extensor $F_{ext}$ and flexor actuators $F_{flex}$, which are calculated by the PMFE. The PSBc is modified based on previous work [270]. Dynamic modelling of the human and robot system is required for the PMFE and the plant dynamics and is explained firstly in section 4.2.2.1. There are two main models in the PSBc, the PMFE and the actuator controller (i.e., the PMAs in Figure 4.2, which is a PMFE based feedforward controller). The PMFE serves as a desired muscle forces generator for the actuators based on the desired joint angles. The PMFE based feedforward force controllers of the antagonistic muscle pairs ensure good force tracking, which will be explained in section 4.2.2.3. The outer position loop between the desired joint angles and the actual joint angles, $\theta_d - \theta$, are responsible for the position tracking performance.

### 4.2.2.1 Dynamic modelling

For the two joint models, the dynamics equation of the two-segment human-robot system is as follows:

$$M(\theta)\ddot{\theta} + C(\theta, \dot{\theta}) + G(\theta) + E = \tau$$

(4.1)

where $\theta$ is the joint angle ($2 \times 1$), $M(\theta)$ is the system mass matrix ($2 \times 2$), $C(\theta, \dot{\theta})$ is the centrifugal and coriolis loading ($2 \times 1$), $G(\theta)$ is the gravity ($2 \times 1$), $E$ is external force and $\tau$ is the net joint torques ($2 \times 1$). Note that this is an estimation of muscle forces during gait swing phase. See equation (3.2) for more details.

### 4.2.2.2 Patient-specific Muscle Force Estimation

The PMFE, which is an inverse dynamics based static optimization model, is to provide reasonable biological commands (i.e., muscle forces) as inputs to control the actuators. As the higher level controller, the PMFE regulates the relationship between forces and motions of the robots just as the impedance controller does [114,
Joint moments of interest are calculated firstly based on the kinematic data, musculoskeletal model, as well as the external forces via the inverse dynamics (4.1). Then the muscle forces are calculated through the static optimization algorithm.

The musculoskeletal model developed in this chapter consists of femur and tibia representing thigh and shank, respectively [81]. *Rectus femoris* (RF) and *biceps femoris* (BF) are chosen to represent knee flexor and extensor. The anatomical parameters such as the segment mass, segments length, muscle moment arms and muscles are taken from the scaled generic musculoskeletal model. The scaled musculoskeletal model, i.e. the patient-specific musculoskeletal model, altered the anthropometry to match the particular patient.

Joint moments are calculated via the inverse dynamics (4.1) based on the patient-specific parameters, such as segment mass \( m \), segment length \( l \), and the proximal segment length from center of mass \( l_c \), which are obtained from the scaled musculoskeletal model.

Muscle forces are then calculated through the static optimization technique. The performance criteria used in this study is based on the sum of forces cube.

\[
G = \text{min} \sum_{i=1}^{m} q_i \cdot (F_i)^3
\]

where \( G \) is the objective function, \( m \) is the number of muscles, \( F_i \) is the muscle forces and \( q_i \) is the optimization weight for each muscle. The muscle forces are sensitive to the optimization weight, which are tuned off-line through genetic algorithm.
4.2.2.3 The PMFE based feedforward controller (PMAs)

The PMFE based feedforward controller (PMAs) ensures the pneumatic muscle actuators produce desired muscle forces, which is calculated by the PMFE. The PMFE based feedforward controller for each of the PMAs improves performance by accurately predicting the exact control requirement and accurately modelling the system. The closed-loop PID controller works on modelling error and disturbances of the whole human-robot system. The desired forces $F_d$, extensor force $F_{ext}$ and flexor force $F_{flex}$, are calculated based on the estimated muscle forces via the PMFE and a nominal force set for both PMAs in order to keep both cables in tension.

Figure 4.3: The PMFE based feedforward controller. The upper block is a brief workflow of the PMFE based feedforward controller. The lower block shows the detail of the feedforward modelling.
\[ F_d = F_{PMFE} + F_n \] (4.3)

where \( F_d \) is the desired force that used to control the PMA, \( F_{PMFE} \) is the muscle force estimated by the PMFE and \( F_n \) is the nominal force in order to keep cables in tension. The force control is realized by regulating the valve areas \( A_v \) of the specific pneumatic air muscle. The closed-loop PID feedback loop works in parallel to handle the errors and make sure the force tracking performance.

The PMA dynamics is explained in detail in [82, 239] (see the lower block of Figure 4.3), which modelled the PMA by force-length-pressure relationship (FLP) and dynamic modelling of fluid flow. The FLP relationship demonstrates the relationship of the three and any one of the parameters could be calculated by the rest of two. Length of the PMA is described by PMA contraction \( \Delta x \). The contraction \( \Delta x \) for each PMA are related to angular position of knee joint \( \theta \), initial contraction at resting position \( x_i \) and the pulley radius \( r \).

\[ \Delta x = x_i + (\theta + \frac{\pi}{4})r \] (4.4)

The dynamic modelling of fluid flow describes the relationship between pressure \((P, \dot{P})\), mass flow rate of air into or out of the PMA \( \dot{m} \) and volume of air inside the PMA \( V \).

\[ \dot{P} = \frac{\gamma RT \dot{m}}{V} - \frac{\gamma P \dot{V}}{V} \] (4.5)

where \( \gamma \) is the ratio of specific heats, \( R \) is the universal gas constant, \( T \) is the gas temperature. The volume \( V \) of the PMA is expressed as a function of contraction \( V(\Delta x) \).

The mass flow rate \( \dot{m} \) is related to the valve area \( A_v \), by

\[ \dot{m}(P_u, P_d) = A_v A(P_u, P_d) \] (4.6)
where

\[
\Lambda(P_u, P_d) = \begin{cases} 
\sqrt{\frac{\gamma R T}{\gamma + 1} \left( \frac{2}{\gamma + 1} \right)^{(\gamma + 1)/\gamma} C_r P_u} & \text{if } \frac{P_d}{P_u} \leq C_r \text{ (choked)} \\
\sqrt{\frac{2\gamma}{RT(\gamma - 1)}} \left[ 1 - \left( \frac{P_d}{P_u} \right)^{(\gamma - 1)/\gamma} \right]^{1/\gamma} C_r P_u & \text{otherwise (unchoked)}
\end{cases}
\] (4.7)

Here \( A_v \) is the valve area, \( P_u \) and \( P_d \) are upstream and downstream pressure. \( C_r \) is the discharge constant and \( C_r \) is the pressure ratio that divides the flow into choke and unchoked flow.

As shown in Figure 4.3, forces \( F \) of the PMA are calculated via the PMA dynamics based the plant dynamics (i.e. the joint angles measured from the position sensors \( \theta, \dot{\theta}, \ddot{\theta} \), pressures \( P \) of the PMA and the valve area \( A_v \)). The plant dynamics is able to calculate PMA contractions \( \Delta x \) by (4.5). Pressure \( P \) of the PMA is calculated through the dynamic modeling of fluid flow (4.6-4.8). Once PMA contraction \( \Delta x \) and pressure \( P \) are obtained, muscle force \( F \) of PMA is calculated. The feedback force loop combined with the desired muscle forces calculated by the PMFE aims to ensure good force tracking performance via the PID controller.

The lower block of Figure 4.3 shows the feedforward algorithm of the PMFE based feedforward controller, which is based on PMA dynamics and the PMFE algorithm. The feedforward algorithm accurately calculates the required valve area \( A_v \) based on the desired joint angle \( \theta_d \). \( \Delta x \) is calculated via (4.4). The required forces are calculated via the PMFE, the inverse dynamics based static optimization algorithm (4.1-4.2). Pressure \( P \) of the PMA is then calculated through the FLP relationship. The valve area \( A_v \) is deducted by (4.7) based on the inputs \( \Delta x \) and \( P \).

\[
A_v = \frac{m(P_u P_d)}{\Lambda(P_u, P_d)}
\] (4.8)
4.3 Evaluation and results

The PSBc is evaluated by both computer simulation and an experiment using HuREx. The protocol, results, and analysis of both simulation and experiment are presented in the following parts.

4.3.1 Computer simulation and results

Gait analysis data from six adolescents (age: 12.9±3.81 years old; leg length: 0.81±0.093 m; weight: 52.62±20.05 Kg) at three speeds, fast, free and slow (1.77±0.43 m/s, 1.09±0.08 m/s and 0.775±0.165 m/s) [250], were used as inputs for simulation.

A generic musculoskeletal model, 3DGaitModel2392 [81], which has 23 degrees of freedom and actuated by 92 muscle-tendon units, was scaled down according to the anthropometric measurement from each subject to represent the patient-specific properties of the subjects. Based on the subject-specific musculoskeletal model, joint angles were calculated through the inverse kinematics pipeline of OpenSim. The joint angles were used as the reference trajectories for the PSBc. The system dynamics and actuator dynamics were estimated based on (4.1-4.8). Subsequently, the joint trajectories of HuREx were simulated by applying the PSBc using Matlab 2012.

The joint angle tracking performance of both simulation and robot experiment is illustrated by coefficient of determination ($R^2$) values and the root-mean-square error (RMSE).
Figure 4.4: Simulation results of the PSBc tracking the reference joint angle at slow speed. The blue curves are reference knee joint angles, and the red curves are the simulation results of the knee joint angles.
Figure 4.5: Simulation results of the PSBc tracking the reference joint angle at free speed. The blue curves are reference knee joint angles, and the red curves are the simulation results of the knee joint angles.
Figure 4.6: Simulation results of the PSBc tracking the reference joint angle at fast speed. The blue curves are reference knee joint angles, and the red curves are the simulation results of the knee joint angles.

Figure 4.4, Figure 4.5, and Figure 4.6 show the performance of the PSBc tracking the reference knee joint angle at slow, free, and fast speeds. The blue curves are the reference knee joint angles, and the red curves are the simulation results of the knee joint angles. All trials are normalized to one gait cycle. The positive values are knee flexion angles, while the negative angles are knee extension angles. The simulation results are calculated when the parameters are set as following: $p_1 = 0.00679$, $p_2 = -10$ for the PMFE and $K_p = 50$, $K_d = 0.2$, $K_i = 0.1$ for the inner PID controller. Table 4.1 shows the knee joint angle tracking performance by means of mean and standard deviation of $R^2$ values and RMSE for six subjects at slow, free and fast speed. The parameter $K_p$ is set at different level to make sure the performance of the PSBc at different compliance level. The smaller the $K_p$ is, the more compliant the system is.
Table 4.1: The PSBc performance

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</tbody>
</table>

Figure 4.4, Figure 4.5, Figure 4.6 and Table 4.1 show that the PSBc has good performance at tracking desired joint angles for all subjects at three speeds. The $R^2$ parameters are greater than 0.97 for all three speeds and the RMSE values of all speeds are from $1.17 \pm 0.34$ degree to $2.55 \pm 0.45$ degree. Note that the mean and SD of ROM for all trials are $59.13 \pm 6.04$ degrees. The knee joint angle tracking performances at different compliant levels are different. $K_p$ is set to 5, 10, 20, 40 and 50. The $R^2$ is increasing when $K_p$ is larger. The $R^2$ values are $0.9760 \pm 0.0084$, $0.9726 \pm 0.0140$, and $0.9769 \pm 0.0101$ at slow, free and fast speed, respectively when $K_p$ equals 5. $R^2$ values are $0.9903 \pm 0.0062$, $0.9893 \pm 0.0071$, and $0.9826 \pm 0.0121$ at slow, free and fast speed respectively when $K_p$ equals 50. RMSE values are decreasing when $K_p$ is larger. The RMSE values are $2.5485 \pm 0.4532$, $2.3830 \pm 0.4573$, and $2.3821 \pm 0.4942$ at slow, free and fast speed.
respectively when $K_p$ equals 5. The RMSE values are $1.3054 \pm 0.2993$, $1.1723 \pm 0.3394$, and $1.5169 \pm 0.4565$ at slow, free and fast speed respectively when $K_p$ equals 50. The knee joint angle tracking performance is better when the walking speed is lower. For example, when $K_p$ equals 50, $R^2$ at slow speed is 0.9903, while $R^2$ at fast speed is 0.9826.

### 4.3.2 Robot experiment and results

The experiment evaluates the ability of the PSBc by tracking a predefined trajectory using HuREx. The experiment was carried out in the mechatronics lab of the University of Auckland. The controller is implemented based on *Labview 2012* and *National Instrument CompactRIO 9072*. A user interface is developed in *Labview 2012* to adjust control parameters and show graphical results such as joint kinematics (angular position and angular velocity), PMA pressure and PMA forces.

During the experiment, the thigh of HuREx was fixed at a steady angle. The shank segment rotated around the knee joint and controlled by the two antagonistic PMAs. A 4kg weight is attached at the end of the shank attachment to simulate the weight of the shank of a normal person. Experiment at a compliant condition is conducted, in which the parameters are set as following: $p_1 = 0.00679$, $p_2 = -10$ for the PMFE and $K_p = 5$, $K_d = 0.2$, $K_i = 0.1$ for the inner PID controller. Six trials are included in this condition. The reference trajectory is a sine wave with mean position of 45 degrees, amplitude of 10 degrees, and the time period of 20 seconds. The sine wave is used as a close representation of human gait trajectory. During the experiment, the PSBc governed the behavior of the HuREx through the extension and flexion PMA by regulating the high-speed solenoid valves. The compressor and the rest of the pneumatic system (see Figure 1) were used to inflate the PMAs. The PMFE of the PSBc calculated the required muscle forces for each PMA. The inner PMFE based
feedforward controller, paralleling with the feedback PID controller, controlled the high-speed solenoid valves to track desired muscle forces in real-time. The PID gains are able to adjust to cope with different compliant requirements.

Figure 4.7 shows the knee angle tracking results and Figure 9 shows the extensor and flexor forces tracking results. Table 2 shows the statistics of the position tracking and force tracking. It is concluded that the desired muscle forces calculated by the PMFE are accurately ($R^2 > 0.998$) for both extensor and flexor, while the position had a relatively worse tracking performance ($R^2=0.87$).

Figure 4.7: Knee angle tracking experiment results. Blue line is the desired knee joint angle. Red lines are averaged actual knee joint angle and SD.
Figure 4.8: The force tracking results from the flexors and the extensors. Red lines are desired extension forces. Blue lines are averaged actual extension forces. Units are $N$.

Table 4.2: The $R^2$ and the averaged RMSE of the knee joint angles and knee flexor and extensor muscle forces.

<table>
<thead>
<tr>
<th></th>
<th>Joint angle $R^2$</th>
<th>Knee extensor muscle force $R^2$</th>
<th>Knee flexor muscle force $R^2$</th>
<th>RMSE</th>
<th>2.04</th>
<th>1.78</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.87</td>
<td>0.999</td>
<td>0.998</td>
<td>3.4</td>
<td>2.04</td>
<td>1.78</td>
</tr>
</tbody>
</table>

### 4.4 Discussion

This PSBc aims to control human-inspired rehabilitation robots based on patients’ own musculoskeletal model and biological command, which is represented by the muscle forces from extensor and flexor muscles. The simulation and preliminary
Patient-specific Neuromusculoskeletal Models

Experiment results show that the robot can track desired position as well as desired muscle force by utilizing the PSBc.

This control scheme is designed for the initial stage of the rehabilitation process to guide human motion following a predefined motion and forces [53-56]. This is called robot-in-charge control scheme (RIC). Unlike conventional RIC controllers, this controller provides accurate patient-specific parameters, which ensure the good performance as well as maximum comfortable. The PMFE model of the PSBc also provides kinetic information from the patient.

The general idea of this controller is starting from and based on the human musculoskeletal system. As indicated by literature and clinical evidences [38, 39], the most important factors of the physical gait rehabilitation training are patient involvement and the intensity of the training.

The PSBc strategy has several advantages:

- Firstly, this controller is based on the patient-specific musculoskeletal model. The dynamic modelling of the patient is regarded as patient-specific. The 3D musculoskeletal model in PSBc provides patient specific anthropometric and anatomy information both in the controller design and the robot design. This is extremely important for building a patient-specific robot [81]. Even though some work has been done to design a robot based on human’s musculoskeletal model [239, 272], they failed to design controllers also based on the musculoskeletal model.

- Secondly, according to the rehabilitation therapy role (task-specific, repeatability and intensity [51]), based on the PMFE, the pneumatic air muscles are actuated in the same manner with the patient’s musculoskeletal model actuation system, which logically will ensure optimal rehabilitation output. Muscle forces used to control the pneumatic muscles calculated by
the PMFE have the same patterns with the muscle activation patterns of both extensor and flexor muscle [179, 185].

In general, human-inspired rehabilitation robots can be controlled by the PSBc. The PSBc is used to displace the user’s shank, along a desired trajectory. The angle tracking results at different compliant levels \( (k_p = 5, 10, 20, 40, 50) \) demonstrate that HuREx can follow the knee joint trajectory given by gait analysis data from literature [19]. The knee tracking result is worse at \( k_p = 5 \) in comparison with that at \( k_p = 50 \). This is expected because the decreased \( k_p \) makes the inner force controller more compliant.

Compared with the simulation results of reference knee joint angle tracking (the average \( R^2 \) is greater than 0.99), the preliminary results of robot experiments showed a worse joint angle tracking performance with the \( R^2 \) values of 0.87. The inaccuracy of the joint angle tracking is mainly due to the inaccuracy modelling of the human-robot system, the difficulty of controlling pneumatic muscle actuators and so on. The system modelling of involves estimation of system inertia, friction and gravity of the dynamic equation (see Equation 4.1). The estimation of system modelling parameters was conducted by experiment measurements and had errors. Thus, the inaccuracy of system dynamic modelling parameters leads to larger joint angle tracking performance. Furthermore, the behaviour of PMAs in the real-world experiment is not ideal and is not fully considered in the control system of the HuREx. For example, the pneumatic air is compressed via an air compressor and then transmitted to the PMAs, which is not accurately modelled and considered. The compressed air into and out of the PMAs is controlled via switching valves based on information from force, pressure, and position sensors.

The preliminary experiments show that the required reference time for one gait cycle is 20 seconds, which is much longer than the stride time of human walking. This is
due to the actuation arrangement of the HuREx. One single large PMA acting as one extensor or flexor required a large amount of air from opening to PMA inflate completely, which causes lag in actuation response and cannot achieve fast movement. In the future, multiple small PMAs acting as the extensor groups or flexor groups are a possible solution to improve the movement speed and also provide enough joint torque for the human-robot system.

Control of systems actuated by PAMs is challenging. Various approaches have been used or proposed, such as conventional PID control [273], modified version of PID control [142], adaptive control [145], controllers based on the computed torque method [146, 147], neural networks [149], sliding mode control (both simulation studies [151] and implementation [152]) and other nonlinear control methods [150, 153], as well as the recently introduced equilibrium point control method [154]. In conventional studies related to PMA, sliding mode controllers have been considered to be the most suitable position controller with respect to minimizing the effort related to complex error dynamics [91]. It is capable of achieving both accuracy and safety. Thus, in order to optimally control the pneumatic air muscles, a better lower level controller such as sliding mode controller will be used in the biological command based controller.

The proposed controller is only valid in swing phase tracking because the external force (i.e. the ground reaction force) is not taken into account in the PMFE. Thus, the desired torque and desired forces are only valid during swing phase. The ground reaction force measurement device such as force plate [274] must be incorporated into the robot’s design.

The PSBc is limited in several aspects. Firstly, this controller is sensitive to the accuracy of kinematic data and the dynamic modelling of the robot. Thus, not only the anatomy parameters but also the dynamic modelling should be as accurate as
possible. Secondly, some parameters such as $q_i$ in the PMFE need to be tuned manually. A self-tuned algorithm is needed to self-adjust different walking speeds. Thirdly, the PSBc does not take into account the interaction between the patient and the robot, and only regard the patient and robot as one system. This affects robot performance. Thus, an improved PSBc controller taking into account the human-robot interaction is also the future work.

4.5 Summary

The PSBc is presented and evaluated in this paper. The PSBc is based on a patient-specific 3D musculoskeletal model, which provides anatomical parameters and time-variable moment arms according to joint angles. The biological commands (i.e., muscle forces calculated by the PMFE based on patient’s musculoskeletal model) are served as control inputs of the PSBc to control the antagonistic air muscles. The PMFE is an inverse dynamics based static optimization method with the aim to control a rehabilitation robot via muscle forces. A PMFE based feedforward controller is used as the lower level force controller to ensure good force tracking performance of the PMAs. The simulation results and the preliminary results of the experiment show that the proposed PSBc has the potential to control rehabilitation robot via muscle forces estimated by the PMFE. Meanwhile, the study also shows the possibility of employing techniques in biomechanics in controlling and designing gait rehabilitation robots.
Patient-specific EMG-driven neuromuscular model for real-time control of gait rehabilitation robots

Although the PMFE calculates individual muscle forces accurately in real-time, it still has the limitations such as highly sensitivity to kinematic data, difficulty to solve co-contraction of movement and neglecting of activation dynamics of muscles. To address this matter, a modified EMG-driven model for the real-time control of gait rehabilitation robots is presented in this chapter.
5.1 Introduction

As summarized in previous chapters, compliant control paradigms [28] or assist-as-needed control paradigms [34] are developed for incorporating patients’ voluntary movement and to activate muscle contribution [275]. Currently, the leading methodologies for realizing these control strategies are through the compliant behaviour of the robots based on kinematic information, kinetic information, or impedance patterns [53-56]. The main limitations of these control strategies are as follows. Firstly, they cannot assess patients’ movement intention at muscle level. Secondly, the anatomical and anthropometric or muscle-related parameters, which are essential for the robotic control algorithm, are not patient-specific.

A logical solution is to develop a patient-centred controller based on the patient’s own musculotendon system, which models the patient accurately and incorporates the patient’s intention. For patients with neurological disorders, EMG signals are one of the most effective ways to identify errors in neurological control, muscle weakness, voluntary substitutions or obligatory posturing through the altered timing and intensity [8]. Thus, EMG-driven models with or without an appropriate musculoskeletal model have been used to represent a patient’s own neuromuscular effort in gait rehabilitation robotic control schemes [23].

Previous EMG-driven lower limb models are usually used to predict joint kinematics [204, 209] and joint kinetics [219] in the area of biomechanics, based on the Hill-type model and iterative algorithms. For instance, Lloyd et al. [204] estimate knee joint moment based on a generic 3D anatomical model, which included 10 and 13 muscles around the knee joint, respectively. They also included 18 adjustable parameters to ensure good moment estimation via an optimization algorithm. The muscle mechanics model they employed is a separated force–length (FL) and force–
velocity (FV) relationship. The model is processed offline using numerical iterative algorithms.

One problem with these physiological models is that they aim to diagnose, manage neurological or orthopedic conditions, or to study human neurological control in clinical applications. Such EMG-driven models cannot be used to control gait rehabilitation robots.

- Firstly, a large part of the muscle mechanics models treat the FL and FV relationship separately [204, 209, 212, 219]. However, it is not physiologically meaningful to use the FL and FV relationships separately, because when the FL property is defined, the FV equation only describes the FV relationship when the muscle is at its optimal length $l_m^0$ [227, 228]. Therefore, the Hill-type muscle mechanics should be described by a combined FLV relationship.

- Secondly, the current iterative algorithms such as the Runge-Kutta-Fehlberg algorithm cannot realize in real time, which is one of the main requirements for the rehabilitation robotic application [229].

- Thirdly, previous EMG-driven models are employed in the area of biomechanics instead of rehabilitation robots. They tend to include as many muscles as possible [208] around each joint with a large number of adjustable parameters to ensure good prediction (such as joint moment). This leads to a longer calculation time or a poor prediction ability for novel data [206].

The patient-specific EMG-driven neuromuscular model (PENm) is developed and presented in this chapter. Besides the inherent requirements for EMG-driven models, the PENm modifies current EMG-driven models for the potential use of gait
rehabilitation robots by decreasing the calculation time and preserving the prediction accuracy.

- To decrease the calculation time as much as possible, the PENm is designed to incorporate EMG channels from two muscles around each joint and minimum physiological parameters. A dynamic computation model is also developed based on Zajac’s computation flowchart [199].

- To preserve the prediction accuracy, the PENm is based on a simplified musculoskeletal model. Accurate patient-specific musculotendon parameters and muscle kinematics (such as the musculotendon lengths and muscle moment arms) during the entire gait cycle are employed based on the musculoskeletal model. An improved FLV relationship is implemented to generate accurate muscle forces. Kinematic data, kinetic data, and EMG signals of knee joint muscles from six healthy subjects [250] are used as the case study to evaluate the effectiveness of the PENm.

5.2 Patient-specific EMG-driven neuromuscular model

The PENm is developed for controlling knee joint flexion and extension movements in the sagittal plane for human-inspired gait rehabilitation robots. According to the robotic application requirements, the proposed model has been modified in terms of minimized subject-specific parameters and muscle channels, modified muscle mechanics relationships and calculation strategy. A Hill-type muscle mechanics model, combined with a 3D motion capture technique and 3D musculoskeletal model, is employed to meet these requirements.
As depicted in Figure 5.1, the PENm consists of four parts: musculoskeletal model, EMG-torque modelling, inverse dynamics and the parameters optimization algorithm. The EMG-torque modelling covers the process from neural excitations of muscles to generation of musculotendon forces and joint moments. The inverse dynamics modelling estimates reference joint moment based on the kinematic data and external loads. The optimization algorithm is used to determine a set of patient-specific parameters, which ensure good joint moment prediction.

In the PENm, a patient-specific musculoskeletal model is developed firstly to provide muscle kinematics (such as the musculotendon lengths $L_{ext}^{mt}$ and $L_{flex}^{mt}$), and muscle moment arms ($r_{ext}$ and $r_{flex}$ from both the extensor muscle and flexor muscle) for contraction dynamics modelling and forward dynamics modelling. The neural excitations of the extensor and flexor muscle group $u_{ext}$ and $u_{flex}$, which are represented by the rectified raw EMG signals, generate muscle activation $a_{ext}$ and $a_{flex}$ through the activation dynamics. These activations develop muscle forces $F_{ext}$ and $F_{flex}$ through the muscle contraction dynamics. Then, the joint moments are developed by forward dynamics. In order to simplify this highly redundant and nonlinear system to cope with the real-time application requirement, one extensor and one flexor muscle are selected to actuate each joint’s extension/flexion movement. The details of all the sub-models are introduced in the following sections.
Figure 5.1: A brief workflow of the PENm. The PENm includes four main models, the patient-specific musculoskeletal model, inverse dynamics, EMG-torque modelling and optimization model.

### 5.2.1 Model inputs

The model inputs include the kinematics data, ground reaction forces, and sEMG signals from the extensor and flexor muscles around the knee joint. Raw EMG signals are rectified, high-pass filtered and low-pass filtered. Then the EMG envelopes of each muscle are normalized by peak values. A scaled 3D musculoskeletal model is regarded as the patient-specific musculoskeletal model to obtain the patient-specific anthropometric, anatomical parameters and muscle kinematics. Only the knee joint is investigated as the case study in this paper.
5.2.2 The patient-specific musculoskeletal model

The PENm is based on the patient’s own musculoskeletal model [81], which consists of the knee joint and knee flexor/extensor muscles (see Figure 5.2). The main knee extensors (rectus femoris (RF), vastus intermedius (VI), vastus lateralis (VL), vastus medialis (VM)) and main knee flexors (biceps femoris caput longum (BFL), biceps femoris caput breve (BFS), semimembranosus (SM), and semitendinosus (ST), are selected to be investigated. The musculoskeletal model is built upon the generic 3D musculoskeletal model in OpenSim and scaled down based on the anthropometric data of the subject and kinematic data from the gait analysis experiment using the 3D motion capture equipment. This simplification is based on the musculoskeletal function during walking and, most importantly, the structure of the human-inspired rehabilitation robots [239], which uses two antagonistic artificial muscles and cables to mimic the human musculoskeletal system.

The musculoskeletal model is the foundation of the PENm modelling. As our purpose is to use the patient’s “intention”, i.e. muscle forces, based on sEMG signals, to control the HuREx, two channels are needed according to the actuation system of the HuREx. Eight main extensors and flexors are investigated first in muscle kinematics and sensitivity analysis in order to understand their muscle kinematics behaviours and EMG-torque behaviours. From these evaluations, two muscles are chosen to represent the knee extensor and knee flexor in order to simplify the musculoskeletal model. Because once the EMG electrodes are settled, a thorough calibration is needed to ensure the good prediction performance of the PENm. The more complicated the system is, the more difficult the calibration process will be. Thus, the simplification makes the system more robust.
5.2.3 The muscle kinematics

Modelling and simulation of PENm require accurate estimation of musculotendon kinematics, including musculotendon length $L_{mt}$ and muscle moment arms $r$. The musculotendon kinematics is firstly produced by OpenSim, which models musculotendon paths wrapping around points and/or surfaces [81, 276] based on the results of the obstacle detection algorithm [2]. In order to obtain the continuously predicted musculotendon kinematics [246, 247], fourth order Fourier equations (5.1) and (5.2) based on the musculotendon length $L_{mt}$ and muscle moment arm $r$ estimated by OpenSim are used to represent the musculotendon length and moment arms for the entire gait cycles.

$$L_{mt} = a_0 + \sum_{i=1}^{4} (a_i \cdot \cos(iwx) + b_i \cdot \sin(iwx))$$  \hspace{1cm} (5.1)
In equation (5.1) and equation (5.2), $x$ is the normalized gait cycle (0%-100%), $a_i, b_i, c_i, d_i, v$, and $w$ are Fourier parameters. For each subject, the musculotendon lengths and moment arms versus normalized gait cycles are calculated offline based on the patient-specific musculoskeletal model and the gait kinematic data. The relationships of the $L^{mt}$ and $r$ from one trial represent those relationships for the subject.

### 5.2.4 EMG-torque modelling

The EMG-torque modelling is based on the musculotendon actuator relationship, the Hill-type muscle mechanics model [200] and the tendon properties [199]. The Hill-type model consists of muscle kinematics, muscle activation dynamics and muscle contraction dynamics. A dynamic computation model (see Figure 5.3), rather than the traditional numerical integration algorithm such as the Runge-Kutta-Fehlberg algorithm [206, 209, 211, 229, 277], is developed for the purpose of rehabilitation robotic applications.

![Figure 5.3: The brief workflow of dynamic calculation model of the PENm](image)

As illustrated in Figure 5.3, the important steps of the PENm calculation include calculating muscle activation levels $\alpha(t)$, muscle forces $F^M$, and tendon length $L^T$. The model inputs are the musculotendon length $L^{MT}$ and the muscle excitations $u(t)$.
from both the extension and flexion muscles. The muscle activations are obtained through the activation dynamics [199] and the nonlinearity modelling [206]. Given that the musculotendon length $L^{MT}$ is obtained through the patient-specific musculoskeletal model, the muscle fibre length $L^M$ and muscle fibre velocity $V^M$ are calculated via the relationship between the musculotendon length, muscle fibre length and tendon length. Based on the muscle activation level, the total muscle force $F^M$ is the sum of the passive muscle force $F^{PE}$ and active muscle force $F^{CE}$ [205]. The active force $F^{CE}$ depends on muscle fibre length $L^M$, velocity $V^M$, and state of activation of the muscle fibres $a(t)$. The passive force $F^{PE}$ depends on muscle fibre length $L^M$. The normalized tendon force $F^T$ is estimated by employing the relationships between the muscle force and tendon force [199]. The tendon length $L^T$ can be deduced from the tendon force-strain relationship, which is the tendon length–force relationship and serves as the input of the first step. Details of the relationships and the corresponding equations are shown in Table 5.1 [199, 205, 206]. The dynamic calculation model is processed by Simulink software for the real-time requirement of the robotic application.
Table 5.1: The musculotendon-actuator relationships and the corresponding equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F_T = F^M \cos \alpha )</td>
<td>( F_T, F^M )</td>
<td>Tendon force/Dimensionless tendon force</td>
</tr>
<tr>
<td>( F_T = F_T^0 \cdot F^M )</td>
<td>( F^M )</td>
<td>Muscle force/Dimensionless muscle force</td>
</tr>
<tr>
<td>( F^M = F_W \cdot F^M_0 )</td>
<td>( F^M_0 )</td>
<td>The maximum isometric force</td>
</tr>
<tr>
<td>( \alpha )</td>
<td></td>
<td>The pennation angle</td>
</tr>
<tr>
<td>( L_{MT} = L_{T}^M + L_{a}^M )</td>
<td>( L_{MT} )</td>
<td>The musculotendon length</td>
</tr>
<tr>
<td>( L_{a}^M = L^M \cos \alpha )</td>
<td>( L_{a}^M )</td>
<td>The tendon length/Dimensionless tendon length</td>
</tr>
<tr>
<td>( L^T = L_{T}^0 \cdot L_{a}^M )</td>
<td>( L^T )</td>
<td>The muscle length/Dimensionless muscle length</td>
</tr>
<tr>
<td>( L_{0}^M = L_{T}^0 \cdot L_{a}^0 )</td>
<td>( L_{0}^M )</td>
<td>The optimal muscle fibre length</td>
</tr>
<tr>
<td>&amp;</td>
<td>( \tau_{act} )</td>
<td>The time constant</td>
</tr>
<tr>
<td>( \beta )</td>
<td></td>
<td>The ratio of the time constant when the muscle is fully activated and fully deactivated</td>
</tr>
<tr>
<td>( e(t) )</td>
<td></td>
<td>The normalized, rectified and filtered EMG signals</td>
</tr>
<tr>
<td>( u(t) )</td>
<td></td>
<td>The muscle activation</td>
</tr>
<tr>
<td>( a(t) = \frac{e^A u(t)}{e^A - 1} )</td>
<td>( A )</td>
<td>The nonlinearity shape factor</td>
</tr>
<tr>
<td>( a(t) )</td>
<td></td>
<td>Muscle activation after nonlinearity</td>
</tr>
</tbody>
</table>
Table 5.1: The musculotendon-actuator relationships and the corresponding equations (continued)

<table>
<thead>
<tr>
<th>Description</th>
<th>Equation</th>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hill-type model basics [206]</strong></td>
<td>( F^M = F^{CE} + F^{PE} )</td>
<td>( F^{CE} )</td>
<td>The active muscle force</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( F^{PE} )</td>
<td>The passive muscle force</td>
</tr>
<tr>
<td><strong>Passive force–length relationship [205]</strong></td>
<td>( F^{PE} = \frac{e^{\alpha F^{CE}}}{e^{\alpha F^{PE}}} )</td>
<td>( \alpha )</td>
<td>The exponential shape factor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \epsilon^M_0 )</td>
<td>The passive muscle strain due to maximum isometric force</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \epsilon^M )</td>
<td>The passive muscle strain</td>
</tr>
<tr>
<td><strong>Active force–length relationship [205]</strong></td>
<td>( f_f = e^{-(\Gamma^M-1)f_f\gamma} )</td>
<td>( \Gamma^M )</td>
<td>Normalized muscle fibre length</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \gamma )</td>
<td>Active force–length shape factor</td>
</tr>
<tr>
<td><strong>Muscle contraction dynamics [205]</strong></td>
<td>( F^{CE} = \frac{\beta_{m-b}}{V_{max}^{(0.25+0.75a)}} + a_f f_f + \left{ \begin{array}{l} a_f + \frac{\beta^{CE}/A_f}{F^{CE} \leq a_f} \vspace{1mm} \frac{\beta^{CE}/A_f}{F^{CE} &gt; a_f} \end{array} \right} )</td>
<td>( f_{lim} )</td>
<td>The fibre length when the muscle force achieves the maximum</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \beta^m )</td>
<td>The muscle fibre velocity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \beta_{max} )</td>
<td>The maximum muscle contraction velocity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( A_f )</td>
<td>The force–velocity shape factor</td>
</tr>
<tr>
<td><strong>The tendon length–force relationship</strong></td>
<td>( l_t^s = \log \left( \frac{F^T - F_{lim}}{k_{lin}} \right) + \epsilon_t^{lin} \ v_t^{lin} + l_t^s / k_{lin} + l_t^s )</td>
<td>( k_{lin} )</td>
<td>Exponential shape factor</td>
</tr>
<tr>
<td></td>
<td>( \left{ \begin{array}{l} 1^{T}<em>{t</em>{lim}} + v_t^{lin} / k_{lin} \ v_t^{lin} \log \left( \frac{F^T - F_{lim}}{k_{lin}} \right) + \epsilon_t^{lin} \ v_t^{lin} + l_t^s / k_{lin} + l_t^s \ F^T \leq 0.33 \vspace{1mm} \left( \frac{F^T - F_{lim}}{k_{lin}} + \epsilon_t^{lin} \right) \ v_t^{lin} + l_t^s + l_t^s \ F^T &gt; 0.33 \end{array} \right} )</td>
<td>( k_{lin} )</td>
<td>Linear scale factor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \epsilon_t^{lin} )</td>
<td>Tendon strain due to maximum isometric force</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \epsilon_t^{lin} )</td>
<td>The tendon strain linear point</td>
</tr>
</tbody>
</table>
Note that a combined FLV relationship (5.3) instead of the separate FL and FV relationship is employed for accurate physiology estimation, which is supported by Sang Hoon Yeo et al. [227]. They used isotonic shortening data from mouse soleus and toad depressor mandibulae muscles to test three Hill-type muscle models (the force-scaling model, the f-max scaling model, and the force-scaling model with parallel spring) by simulating the shortening dynamics of the muscle. The results show that the force-scaling model we normally used is less accurate.

The normalized active muscle force $F_{CE}$ is expressed as a function of the muscle fibre velocity $V^m$, muscle fibre length $l^m$ and the muscle activation $a$ [205]. In equation (5.3), $V_{m}^{\infty} = \frac{V_m}{V_{max}}$ is the dimensionless muscle fibre velocity and $f_l$ is the active FL relationship, which is represented by a Gaussian function [278].

$$F_{CE} = \frac{V^m \cdot b}{V_{m}^{\infty} \cdot (0.25 + 0.75a)} + af_l$$

and $b = \begin{cases} \frac{af_l + F_{CE}/A_f}{1 + \frac{F_{len} - F_{CE}}{F_{len}}} & F_{CE} \leq af_l \\ \frac{2 + 2/A_f}{(2 + 2/A_f)(af_l F_{len} - F_{CE})} & F_{CE} > af_l \end{cases}$

(5.3)

The tendon length-force relationship (details are in Table 1) is

$$l_t = \begin{cases} l_T \cdot \epsilon_{toe} \cdot k_{toe} \cdot \log \left( \frac{F_T - \epsilon_{toe} \cdot l_T}{F_{toe}} \right) + 1 \right) \cdot \epsilon_{toe} \cdot l_T^s / k_{toe} + l_T^s; F_T \leq 0.33 \\ (\frac{F_T - F_{toe}}{k_{lin}} + \epsilon_{toe} \cdot l_T^s + l_T^s; F_T > 0.33 \end{cases}$$

(5.4)

**5.2.5 Global optimization based on Simulink-M**

The optimization procedure aims to identify a set of subject-specific musculotendon (MT) parameters that ensure the optimal performance at three different speeds, slow,
free and fast. The algorithm minimizes the difference between the joint moment calculated by the PENm and the experiment joint moment.

The optimization problem is solved by the simulated annealing algorithm [204]. The objective function of the PENm global optimization algorithm is

$$\text{Obj} = \frac{\sum_{i=1}^{n} \left( \frac{(M_{\text{sim}} - M_{\text{exp}})^2}{m} \right)}{3n}$$  \hspace{1cm} (5.5)

where $i$ is the different experimental trials, $M_{\text{sim}}$ is the joint moment calculated by the PENm and $k$ stands for the three speeds, $M_{\text{exp}}$ is the reference experimental joint moment, which is calculated by inverse dynamics.

$$M_{\text{exp}} = M(\theta) \dot{\theta} + C(\theta, \dot{\theta}) + G(\theta) + E$$  \hspace{1cm} (5.6)

where $\theta$ is the joint angle, $M(\theta)$ is the system mass matrix, $C(\theta, \dot{\theta})$ is the centrifugal and Coriolis loading, $G(\theta)$ is the gravity, and $E$ represents the ground reaction force.

### 5.3 Sensitivity analysis and model evaluation

The gait data collected from a previous study [250], including kinematics, ground reaction forces, raw EMG signals from six healthy adolescents (age: 12.9±3.81 years; leg length: 0.81±0.093 m; weight: 52.62±20.05 kg) at three different speeds, fast, free and slow (1.77±0.43 m/s, 1.09±0.08 m/s and 0.775±0.165 m/s), were used to analyse the sensitivity of the MT parameters to the joint torque and evaluate the PENm. The ground reaction forces were sampled at 1080 Hz and low-pass filtered at 20 Hz. Raw EMG signals were normalized by the peak value recorded over all walking speeds for a given adolescent to make sure that the muscle activation is between 0 and 1. The normalized raw EMG signals were processed by full wave rectification, high-pass filter (second order Butterworth filter with a cut-off
frequency at 20 Hz) and low-pass filter (second order Butterworth filter with a cutoff frequency at 6 Hz).

5.3.1 Sensitivity analysis of the MT parameters to the joint torque

The sensitivity analysis of the MT parameters is to find a minimum set of parameters in order to be computationally efficient. The algorithm in [279] evaluates the muscle contribution to the joint torque, which determines the gait pattern:

\[ MS_{ijk} = \frac{(M_{+\Delta p,ij} - M_{\Delta p,ij})/2}{\Delta p_k/P_{nom,k}} \]  

Where \( MS_{ijk} \) is the sensitivity of the MT parameters, \( \Delta p_k/P_{nom,k} \) is the relative parameter deviation, \( M_{+\Delta p,ij} \) and \( M_{\Delta p,ij} \) are the perturbed contributions of muscle \( j \) to parameter \( k \) at the time instant \( i \). Sensitivities were averaged over the gait cycle. \( MS_{ijk} < 5Nm, 5 \leq MS_{ijk} < 10Nm \) and \( MS_{ijk} > 10Nm \) for the parameters with respect to their sensitivities were set as low, medium and high. The parameters with higher sensitivity levels require greater accuracy in the PENm.

Twelve MT parameters of eight knee flexion/extension muscles are investigated. The nominal values of these parameters from selected knee extensors such as RF, VI, VL, VM, and knee flexors such as BFL, BFS, SM, and ST are shown in Table 5.2. Moreover, in order to evaluate the sensitivities of the inputs to the joint torque, the muscle excitation \( a(t) \), the musculotendon length \( L^{MT} \), and the moment arms \( r \) of selected muscles are investigated. This sensitivity analysis is based on one gait trial from subject 05. The results of sensitivities to the MT parameters are shown in Table 5.3 and Figure 5.4. As demonstrated in Figure 5.4, low sensitivity is represented as color blue to green, medium is represented as green to yellow, and high is shown as yellow to red.
Table 5.2: The nominal values of the knee extensors and flexors derived from the scaled musculoskeletal model of one subject

<table>
<thead>
<tr>
<th>Flexors</th>
<th>Extensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF</td>
<td>BFL</td>
</tr>
<tr>
<td>VI</td>
<td>BFS</td>
</tr>
<tr>
<td>VM</td>
<td>SM</td>
</tr>
<tr>
<td>VL</td>
<td>ST</td>
</tr>
<tr>
<td>$F_0^M$ (N)</td>
<td>1169</td>
</tr>
<tr>
<td>$L_0^M$ (m)</td>
<td>0.1089</td>
</tr>
<tr>
<td>$l_s^M$ (m)</td>
<td>0.2961</td>
</tr>
<tr>
<td>$K^{PE}$</td>
<td>5</td>
</tr>
<tr>
<td>$\varepsilon_0^M$</td>
<td>0.6</td>
</tr>
<tr>
<td>$\alpha$ (Degree)</td>
<td>0.0872</td>
</tr>
<tr>
<td>$A_f$</td>
<td>0.3</td>
</tr>
<tr>
<td>$f_{len}$</td>
<td>1.8</td>
</tr>
<tr>
<td>$\tau$</td>
<td>0.01</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.04</td>
</tr>
<tr>
<td>$\varepsilon_0^T$</td>
<td>0.033</td>
</tr>
<tr>
<td>$A$</td>
<td>-2</td>
</tr>
</tbody>
</table>

The sensitivity analysis shows that the calculated knee joint torque during gait has a high or medium sensitivity to only a few of the MT parameters for the eight knee flexors and extensors. The sensitivities to tendon slack length $l_s^M$, optimal muscle fibre length $L_0^M$ and the maximum isometric force $F_0^M$ are high. Besides, the knee joint torque has a medium sensitivity to the nonlinear factor $A$ and the ratio $\beta$ between the activation time constant and the deactivation time constant. The knee joint torque also shows high sensitivity to the model inputs (the musculotendon length $L^{MT}$, muscle activation $a(\tau)$ and the muscle moment arms $\tau$), which means that the inputs should be evaluated carefully and be as accurate as possible.
Table 5.3: Sensitivities to the MT parameters

<table>
<thead>
<tr>
<th>Sensitivities Ms (Nm)</th>
<th>RF</th>
<th>VI</th>
<th>VM</th>
<th>VL</th>
<th>BF</th>
<th>BFS</th>
<th>SM</th>
<th>ST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activation dynamics</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Activation Time</td>
<td>9.35</td>
<td>7.75</td>
<td>7.92</td>
<td>7.86</td>
<td>6.07</td>
<td>3.59</td>
<td>6.07</td>
<td>3.46</td>
</tr>
<tr>
<td>Constant $\tau_{act}$</td>
<td>8.63</td>
<td>7.15</td>
<td>7.31</td>
<td>7.26</td>
<td>5.61</td>
<td>3.31</td>
<td>5.61</td>
<td>3.19</td>
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<tr>
<td>$\beta$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Nonlinearity</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Nonlinear Scale Factor $A$</td>
<td>0.95</td>
<td>1.08</td>
<td>0.74</td>
<td>1.78</td>
<td>1.12</td>
<td>0.60</td>
<td>1.12</td>
<td>0.37</td>
</tr>
<tr>
<td>Contraction dynamics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_f$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Passivity</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>$f_{len}$</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Passive force–length</td>
<td>0.12</td>
<td>0</td>
<td>0.10</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.13</td>
</tr>
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<td>relationship</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K^{PE}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Musculo-tendon</td>
<td>17.39</td>
<td>26.96</td>
<td>27.39</td>
<td>27.67</td>
<td>22.28</td>
<td>12.31</td>
<td>22.28</td>
<td>11.95</td>
</tr>
<tr>
<td>actuator property</td>
<td>11.60</td>
<td>18.39</td>
<td>12.12</td>
<td>26.64</td>
<td>18.68</td>
<td>10.18</td>
<td>18.68</td>
<td>2.03</td>
</tr>
<tr>
<td>$\varepsilon_0^M$</td>
<td>0.002</td>
<td>0</td>
<td>0.001</td>
<td>0.008</td>
<td>0.115</td>
<td>0.017</td>
<td>0.115</td>
<td>0</td>
</tr>
<tr>
<td>Contraction dynamics</td>
<td>0.38</td>
<td>0.28</td>
<td>0.15</td>
<td>0.68</td>
<td>0.98</td>
<td>0.06</td>
<td>0.98</td>
<td>0.02</td>
</tr>
<tr>
<td>$\varepsilon_0^T$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tendon properties</td>
<td>24.44</td>
<td>37.83</td>
<td>20.33</td>
<td>89.62</td>
<td>120.79</td>
<td>7.60</td>
<td>120.80</td>
<td>2.30</td>
</tr>
<tr>
<td>$L_0^T$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model inputs</td>
<td>11.70</td>
<td>9.69</td>
<td>9.9</td>
<td>9.83</td>
<td>7.60</td>
<td>4.49</td>
<td>7.59</td>
<td>4.33</td>
</tr>
<tr>
<td>$a(t)$</td>
<td>111.48</td>
<td>55.43</td>
<td>32</td>
<td>114.98</td>
<td>135.22</td>
<td>17.11</td>
<td>135.22</td>
<td>3.52</td>
</tr>
<tr>
<td>$L_{MT}$</td>
<td>32.74</td>
<td>26.96</td>
<td>27.39</td>
<td>27.67</td>
<td>22.28</td>
<td>12.31</td>
<td>22.28</td>
<td>11.95</td>
</tr>
</tbody>
</table>
Figure 5.4: Sensitivities to MT parameters of knee flexors and extensors. Low sensitivity is represented as colour blue to green, medium is represented as green to yellow, and high is shown as yellow to red.

Based on the results of sensitivity analysis, the muscle parameters, including $L^M$ and $r$ for each muscle, are determined through the obstacle detection algorithm combined with the Fourier equations based on the musculoskeletal model via OpenSim. The $l_s$ and $L_0^M$ are obtained from the patient-specific musculoskeletal model. Parameters $A$ and $F^M_0$ are set as the adjustable parameters in the optimization algorithm. The rest of the MT parameters are set using constant values from the patient-specific musculoskeletal model (see Table 5.2).

After the muscle kinematics and sensitivity analysis evaluations, BFS and RF are selected as the flexor and extensor channels for the PENm for the following reasons. Firstly, BFS and RF can represent the EMG-torque behaviours of the knee flexors and extensors. Secondly, BFS and RF are the strongest knee flexor and extensor. Thirdly, BFS and RF are superficial muscles and the muscles’ areas are large, which make it easy to attach the EMG electrode.
5.3.2 Model evaluation of the PENm

The PENm is evaluated by comparing joint moments calculated through the PENm and the experimental joint moments [204]. Table 5.4 and Figure 5.5 show that the PENm can estimate knee joint movement at different speeds (low, free and fast) by only the EMG signals from one knee extensor and one knee flexor muscle via the correlation coefficient $R$, and the averaged RMSE of the joint moments calculated by the two methods. The simulation results of the PENm match well with the reference moments after the MT parameter optimization. The correlation coefficients $R$ are $0.91 \pm 0.046$, $0.90 \pm 0.070$, and $0.91 \pm 0.059$ at low, free and fast speed. The RMSEs are $3.28 \pm 1.40$, $3.87 \pm 1.31$ and $4.85 \pm 1.54$ at low, free and fast speed. The calculation time of the PENm is $0.025 \pm 0.003$ seconds, which shows the potential of realizing real-time calculation for the rehabilitation robot control.
Figure 5.5: The simulation result of the joint moment calculated by the proposed patient-specific EMG-driven musculoskeletal model (Red curve) and the reference joint moment calculated by the inverse dynamics (Blue curve).
Table 5.4: Statistics of the simulation results

<table>
<thead>
<tr>
<th>Subject</th>
<th>( R )</th>
<th>( RMSE )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slow</td>
<td>Free</td>
</tr>
<tr>
<td>01</td>
<td>0.90</td>
<td>0.93</td>
</tr>
<tr>
<td>02</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>03</td>
<td>0.92</td>
<td>0.77</td>
</tr>
<tr>
<td>04</td>
<td>0.97</td>
<td>0.94</td>
</tr>
<tr>
<td>05</td>
<td>0.84</td>
<td>0.96</td>
</tr>
<tr>
<td>06</td>
<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td>Mean</td>
<td>0.91</td>
<td>0.90</td>
</tr>
<tr>
<td>SD</td>
<td>0.046</td>
<td>0.070</td>
</tr>
</tbody>
</table>

5.4 Discussion

The PENm aims to provide patient-specific control signals (i.e. muscle forces and joint moments) based on the patient’s surface EMG signals for the potential use of gait rehabilitation robots. The results (see Figure 5.5 and Table 5.4) show that the PENm is able to predict knee joint moment at three different speeds in real-time based on EMG signals from one knee extensor and one flexor muscle. The correlation coefficients between the simulation results and the experimental reference are greater than 0.91, which is an acceptable accuracy when comparing with results from other researchers [204, 206, 219]. As described in previous research [204, 206, 209, 219], the mean \( R^2 \) values between the estimated knee joint moments and those calculated via inverse dynamics are around 0.91. For previous models [204, 206, 209, 219], they take at least several minutes to predict joint moments from EMG signals depending on the different complexity of musculoskeletal models they used. The calculation time for the PENm is 0.025 ±
0.003 seconds. The results demonstrate that the PENm model provides a potential solution to incorporate patient’s movement intention in gait rehabilitation robots.

The human-inspired rehabilitation robotic application puts forward two requirements for the PENm: real-time calculation and accuracy. The proposed PENm has made the following improvements:

- Employing a patient-specific musculoskeletal model to generate accurate physiological parameters, anthropometric parameters, time-varying musculotendon length and muscle moment arms via OpenSim.
- Implementing a combined FLV relationship.
- Reducing the muscles channels to two and the MT parameters to two.
- Using Simulink as a tool instead of the numerical integration algorithm for calculation.

Unlike the previous EMG-driven models [212], the PENm incorporates a closed-loop parameter optimization algorithm for the gait rehabilitation robots, which has EMG sensors, kinetic-related sensors and ground reaction force sensors. Thus, this model has the potential to calibrate the MT parameters to adapt to different speeds in real-time and control the robotic actuators based on the EMG signals at the same time.

The sensitivity analysis was employed to define the minimum MT parameters, which are helpful to simplify the calculation process and at the same time preserve the estimation accuracy to the utmost. For those parameters or inputs with low sensitivity, They are set as nominal values. For those parameters or inputs with high sensitivity, patient-specific parameters plus global optimization algorithm are used in order to find the optimal parameters.
Besides the musculotendon parameters Scovil and Ronsky tested in their study [279], three model inputs (the muscle excitation, musculotendon length and the moment arms) are also analysed. The author finds that the joint moment is extremely sensitive to musculotendon length, which proves that the accuracy of the MT length $L^{MT}$ is the most important factor. Once the MT length is determined accurately, the properties of the PENm are somehow guaranteed. The reason is that the muscle passive element and the in-parallel contractile element contributing to the muscle forces are governed by the FLV relationship [199]. The FLV relationship is based on the muscle fibre length, and muscle fibre velocity, which is derived from the MT length. However, measuring the MT length in real time is challenging. Massimo Sartori et al. propose a computationally inexpensive method to estimate the length and 3D moment arms using multidimensional B-splines and shows good results for the integration into large-scale neuromusculoskeletal models [280].

Modelling the MT length and moment arms against the joint angle is complex because the relationships of some muscles such as SM, BFL and RF are governed by different MT length-knee angle relationships during knee flexion and extension. In specific, the knee joint, or the tibiofemoral joint, is not a simple hinge joint but a double condyloid joint or a modified hinge joint that combines a hinge and a pivot joint. In the knee joint, flexion is accompanied by a small but significant amount of rotation [253]. The musculotendon lengths are functions of the gait cycle (normalized to 100 frames) instead of the joint angle. Thus, fourth order Fourier equations based on the obstacle detection [246] technique conducted by OpenSim [2] are used to represent the MT length and the moment arms.

There are many limitations in using separate FL and FV relationships to represent Hill-type muscle mechanics despite the positive evidence. The most important is that after the FL property is defined, the FV equation only describes the FV relationship
when the muscle is at its optimal length $L^0_0$ [227]. It is inaccurate and non-physiological to use the FL and FV relationships separately. Yeo et al.’s experiment and analysis on Hill-type phenomenological models support that the force scaling with parallel spring and “f-maxing scaling” model are better representations of the FLV relationship [227], which is implemented in our paper.

In order to achieve real-time calculation, the number of muscles and the MT parameters are simplified. Previous studies include more MT units in the EMG-driven models. For instance, 34 MT units were used to estimate joint moment and forces in the lower extremity [212]. However, given the numerical integration algorithm and the tuning algorithm used for each step or each trial, it is impossible to achieve real-time calculation. Researchers also tend to include more MT parameters to ensure good prediction. For example, Lloyd et al. [204] used 18 adjustable MT parameters in the calibration process. Besides the physiological MT parameters and activation dynamics parameters, Pau et al. introduced damping factors, passive elastic properties and so on to ensure good prediction [219]. Evidently the more adjustable the parameters, the better the fit will be between the estimated joint moment and the measured joint moment. However, models having many parameters have little predictive ability [206]. Ideally, models should be as simple as is reasonable. The fewer parameters that are adjusted, the more faith can be put in the biomechanics undergirding the fitting [281]. Therefore, the proposed PENm has only two adjustable parameters, the nonlinearity factor and the maximum isometric force.

There are several limitations of the current study and future work is needed. The first step is to improve the proposed model by comparing different combined FLV relationships, taking into account the muscle synergy [282] and developing an online optimization algorithm. The second step is to employ the proposed model in patients with neurological disorders. For each subject walking at a natural speed, more gait
cycles will be included. The third step is to develop a patient-specific EMG-driven human-robot interaction control scheme and conduct experiments on the human-inspired gait rehabilitation robot.

5.5 Summary

A patient-specific EMG-driven neuromuscular model is proposed and evaluated in this paper. To meet the requirements of the potential use of human-inspired gait rehabilitation robots, the patient-specific musculoskeletal model is designed to incorporate two EMG channels from two muscles around each joint to fit the actuator system of the human-inspired gait rehabilitation robots and reduce the calculation time. A minimum set of patient-specific parameters, which are based on the results of sensitivity analysis, and the dynamic calculation optimization algorithm make real-time calculation plausible. The simulation results show that the PENm can predict accurate joint moment in real-time based only on two EMG channels from one extensor and one flexor muscle and the minimum adjustable parameters. The design of advanced human-robot interaction control strategies and human-inspired gait rehabilitation robots can benefit from the application of the human internal state provided by the PENm.
Evaluation of the patient-specific EMG-driven neuromuscular model for clinical populations

Muscle forces during walking are able to be estimated solely from surface EMG signals in vivo via the proposed patient-specific EMG-driven neuromuscular model (PENm), which gives information on muscle function in addition to traditional gait analysis methodologies. The PENm was evaluated by using gait analysis data from healthy adolescents. In this chapter, experiments using 3D motion capture system, ground reaction force recording system, and surface EMG recording system were carried out on cerebral palsy patients to evaluate the PENm.
6.1 Introduction

A *patient-specific EMG-driven neuromuscular model* (PENm) [283] is developed to estimate joint moment and individual muscle forces around knee joint based solely on EMG signals. The PENm is a modified *Hill-type model* [201-203] designed for robotic applications. The PENm is evaluated by using gait analysis data from healthy adolescents. The PENm is proved that it can predict knee joint moment and muscle forces with good accuracy and computational efficiency. In order to evaluate the ability of the PENm for neurological disorder subjects, a gait analysis experiment on *cerebral palsy* (CP) patients is conducted for recording the gait analysis data including kinematics, kinetic and raw EMG signals from selected muscles.

Gait analysis is a quantitative functional assessment technique for patients with neurological disorders. One of the most successful applications of gait analysis is assisting in CP treatments. CP is the most common motor control impairment in childhood, which can impede both neurological and musculoskeletal development, and may result in abnormal movements. Depending on the severity of involvement, patients show different types of typical gaits, such as *toe-walking* or *crouch gait*. Gait analysis is a quantitative tool for children with CP and is used to evaluate both preoperative surgical planning and postoperative evaluation of the efficacy of various treatment protocols [284]. Compared with traditional clinical assessment methods (e.g. measures of passive range of motion and muscle tone), which are often more subjective or qualitative, gait analysis is an objective approach to assess locomotor functions [285].

Despite the success of modern gait analysis, there are some limitations concerning the role of gait analysis in the overall assessment of patients with CP [286]. Current biomechanical models used in gait analysis are not allowed for studying muscle structure or functioning in detail. Therefore the clinical application has been limited.
Computational models of the musculoskeletal system have the potential to identify abnormally functioning muscles and predict the optimal surgical procedure based on data from clinical gait analysis [206, 287, 288].

In this chapter, a pilot study of using the PENm to investigate muscle functions for CP with crouch gait was described. The clinical gait data is from Shanghai Sunshine Rehabilitation Center (Shanghai, China). I got the permission to use the data according to the collaboration agreement between my supervisor and the rehabilitation center.

In summary, this chapter evaluates the PENm through the following two aspects: prediction of accurate joint moments for CP patients via two EMG signals and providing more in-depth information about the muscle functions for CP patients during crouch gait.

### 6.2 Experiment evaluation

The evaluation procedures consist of three steps (see Figure 6.1). The first step is collecting 3D gait analysis data as well as raw EMG signals using a motion capture system, force plates and wireless EMG sensors. This step has two purposes: (1) to provide measured anatomical locations for building a patient-specific 3D musculoskeletal model for CP patients, and (2) to provide an experimental reference for evaluating the PENm. The second step is building the patient-specific 3D musculoskeletal model for CP patients to obtain accurate anthropometric data, anatomical data, musculotendon parameters and muscle kinematics. The third step is estimating and evaluating joint moment as well as muscle forces by the PENm.
Figure 6.1: A brief workflow of data collection and the PENm evaluation

### 6.2.1 Participants

Four CP patients (1 girl and 3 boys), between 12 and 15 years old, with the gross motor function classification system (GMFCS) ranked at class I [289], participated in this study. Demographic information of these subjects is listed in Table 6.1. The gait assessment protocol was approved by Shanghai Sunshine Rehabilitation Center’s Human Research Ethics Committee. 38 typically developing (TD) children, aged between 8 and 14 years old, adopted from Schwartz and Rozumalski’s study [290, 291], are used as reference joint angles.
Table 6.1: Demographics of participants

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Age</th>
<th>Body weight (Kg)</th>
<th>Foot length (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Left</td>
</tr>
<tr>
<td>1</td>
<td>Male</td>
<td>13</td>
<td>51</td>
<td>245</td>
</tr>
<tr>
<td>2</td>
<td>Male</td>
<td>15</td>
<td>48</td>
<td>245</td>
</tr>
<tr>
<td>3</td>
<td>Female</td>
<td>12</td>
<td>46</td>
<td>224</td>
</tr>
<tr>
<td>4</td>
<td>Male</td>
<td>12</td>
<td>30</td>
<td>202</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td>13</td>
<td>43.75</td>
<td>229</td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td>1.41</td>
<td>9.39</td>
<td>20.54</td>
</tr>
</tbody>
</table>

### 6.2.2 Experiment protocol

An eight-infrared-camera motion capture system (Oxford Metrics Group, Oxford, UK) was used to record the participants’ kinematic data in 3D space. Ground reaction forces were measured by three separate force plates (AMTI OR6 Series). Kinematic data was collected at a frequency of 100Hz and ground reaction forces were measured synchronously at a sampling rate of 1000Hz.

EMG signals were recorded by eight wireless EMG sensors (Noraxon DTS) at a sampling rate of 1500 Hz. Note that these three force plates recorded two gait cycles (right limb gait cycle and left limb gait cycle) in one trial. Spherical reflective markers with a diameter of 14mm were attached to each participants following the *modified Cleveland Clinic marker set* [292]. Markers were placed on both of the acromio-clavicular joints, elbows, wrists, triceps, sacrum, left and right anterior superior iliac spines, thighs (cluster markers), lateral and medial condyles of the knee, shanks (cluster markers), lateral and medial malleoli of the ankle, and each calcaneus and the second metatarsal head of both feet. Details are showed in Figure 6.2. The red circles are reflective markers and the blue rectangles are EMG electrodes. The EMG electrodes are placed on *rectus femoris* (RF), *vastus lateralis*
(VL), *biceps femoris* (BF), and *gastrocnemius* (GA) on both sides of limbs (left and right). Details of the marker set and the EMG electrode placement are listed in Table 6.2 and Table 6.3.

Before experiments began, each participant was given enough time to be comfortable with walking with these markers and EMG electrode (normally five minutes). A static trial was then recorded, during which each participant was required to maintain a static standing posture for a few seconds. Afterwards, each participant was required to walk at a self-selected, consistent speed. Each participant was asked to perform 10 acceptable trials by walking over the force plates. An acceptable trial refers that only one foot touches one force plate, all markers’ position are recorded during the trial and the EMG signals are not beyond saturations.
Figure 6.2: The marker set and EMG electrode placement
Table 6.2: The positions of the Cleveland Clinic markers

<table>
<thead>
<tr>
<th>Location</th>
<th>Markers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper body</td>
<td></td>
</tr>
<tr>
<td>Shoulder</td>
<td>Acromion process</td>
</tr>
<tr>
<td>Arms</td>
<td></td>
</tr>
<tr>
<td>Triceps</td>
<td>Muscle belly</td>
</tr>
<tr>
<td>Elbow</td>
<td>Lateral epicondyle</td>
</tr>
<tr>
<td>Wrist</td>
<td>Posterior aspect (in anatomical position)</td>
</tr>
<tr>
<td>Pelvis</td>
<td></td>
</tr>
<tr>
<td>ASIS</td>
<td>Anterior superior iliac spine</td>
</tr>
<tr>
<td>Sacrum</td>
<td>The midpoint of posterior superior iliac spine</td>
</tr>
<tr>
<td>Thigh</td>
<td></td>
</tr>
<tr>
<td>Triads</td>
<td>Any position on lateral aspect</td>
</tr>
<tr>
<td>Shank</td>
<td></td>
</tr>
<tr>
<td>Triads</td>
<td>Any position on lateral aspect</td>
</tr>
<tr>
<td>Knee</td>
<td>Medial and lateral epicondyle</td>
</tr>
<tr>
<td>Ankle</td>
<td>Medial and lateral malleolus</td>
</tr>
<tr>
<td>Foot</td>
<td></td>
</tr>
<tr>
<td>Heel</td>
<td>Posterior aspect of heel</td>
</tr>
<tr>
<td>Forefoot</td>
<td>Head of the 2nd metatarsal</td>
</tr>
</tbody>
</table>
Table 6.3: The positions of the EMG electrodes [7]

<table>
<thead>
<tr>
<th>Muscle</th>
<th>Anatomical landmarks and reference line</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biceps femoris</td>
<td>The percentage distance (35.3 ± 6.8 %) from the ischial tuberosity to the lateral side of the popliteus cavity, starting from the ischial tuberosity</td>
</tr>
<tr>
<td>Tibialis anterior</td>
<td>The percentage distance (15.5 ± 4.2 (%)) from the tuberosity of tibia to the inter-malleoli line, starting from the tuberosity of tibia</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>The line (50 %) from anterior spina iliaca superior to superior part of petella</td>
</tr>
<tr>
<td>Vastus lateralis</td>
<td>The distance (94 ± 13.2 mm) along a line from the superior lateral side of the patella to the anterior superior iliac spine, starting from the patella</td>
</tr>
</tbody>
</table>

6.2.3 Date processing

The data processing procedure is shown in Figure 6.1. Kinematic and kinetic data are processed by VICON Nexus software firstly (Version 1.8.5, Oxford Metrics, Oxford). Markers are labelled according to the definitions in the modified Cleveland Clinic marker set [292] (Figure 6.2). Segment trajectories and ground reaction forces are filtered using a fourth-order zero-lag Butterworth filter with a cut-off frequency at 6 Hz. Joint kinetics (joint angle, joint velocity and acceleration) and kinematics (reaction force and moments) at all joint are calculated through inverse kinematics and inverse dynamics [245]. Markers’ trajectories of static trial and dynamic trials are extracted to determine the patient-specific musculoskeletal model for CP patients in OpenSim. The OpenSim 3DGaitModel2392 generic model [81] is scaled based on
the markers’ positions during the static trial. *Inverse kinematics* and *muscle analysis* tools are then used to obtain patient-specific muscle kinematics (i.e. musculotendon length, muscle moment arms from selected muscles).

With model inputs (raw EMG signals, musculotendon length, muscle moment arms and musculotendon parameters), the PENm estimates joint moment and muscle forces via *activation dynamics* and muscle *contraction dynamics*. Parameters of the PENm are optimized using *Genetic Algorithm* (GA) to find the patient-specific parameters.

6.3 Results

6.3.1 Simulation results

Figure 6.3 and Table 6.4 show results of knee joint moment prediction via the PENm model. The *coefficient of determination* ($R^2$) and the *root-mean-squared-error* (RMSE) between the knee joint moment calculated by the PENm and the experimental knee joint moment are 0.86±0.06 and 0.09±0.05 Nm/Kg. The maximum knee joint moment via calculated by the PENm is 0.74±0.36 Nm/Kg and the maximum experimental knee joint moment is 0.76±0.41 Nm/Kg. The minimum knee joint moment calculated by the PENm is -0.18±0.06 Nm/Kg and the minimum experimental knee joint moment is -0.29±0.15 Nm/Kg.

Knee extensor (represented by VL) and flexor (represented by BF) muscle forces calculated by the PENm compared with raw EMG signals are showed in Figure 6.4. The maximum and minimum extensor forces are 14.68 N/Kg and 1.29 N/Kg. The maximum and minimum flexor forces are 9.40 N/Kg and 1.32 N/Kg.
Figure 6.3: Knee joint moments of CP patients in sagittal plane via the PENm (Red) in comparison with the experimental knee joint moment (Green). Knee joint moments are normalized by body weight. The units are Nm/Kg. Gait cycles are normalized to 100 frames.
Figure 6.4: Averaged muscle forces from extensor muscle (VL) and flexor muscle (BF) in comparison with the corresponding raw EMG signals. Muscle forces are normalized by CP subjects’ body weight. The units are N/Kg.
Table 6.4: Statistics of knee joint moment via the PENm in comparison with the experimental knee joint moment*.

<table>
<thead>
<tr>
<th>Gait cycle</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>Max Sim</th>
<th>Max Exp</th>
<th>Min Sim</th>
<th>Min Exp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.87</td>
<td>0.09</td>
<td>0.72</td>
<td>0.54</td>
<td>-0.23</td>
<td>-0.35</td>
</tr>
<tr>
<td>2</td>
<td>0.91</td>
<td>0.05</td>
<td>0.71</td>
<td>0.43</td>
<td>-0.15</td>
<td>-0.42</td>
</tr>
<tr>
<td>3</td>
<td>0.93</td>
<td>0.07</td>
<td>0.76</td>
<td>0.83</td>
<td>-0.15</td>
<td>-0.21</td>
</tr>
<tr>
<td>4</td>
<td>0.86</td>
<td>0.10</td>
<td>0.70</td>
<td>0.74</td>
<td>-0.22</td>
<td>-0.23</td>
</tr>
<tr>
<td>5</td>
<td>0.93</td>
<td>0.13</td>
<td>1.22</td>
<td>1.46</td>
<td>-0.21</td>
<td>-0.20</td>
</tr>
<tr>
<td>6</td>
<td>0.84</td>
<td>0.20</td>
<td>1.14</td>
<td>1.30</td>
<td>-0.22</td>
<td>-0.18</td>
</tr>
<tr>
<td>7</td>
<td>0.74</td>
<td>0.06</td>
<td>0.24</td>
<td>0.34</td>
<td>-0.07</td>
<td>-0.14</td>
</tr>
<tr>
<td>8</td>
<td>0.82</td>
<td>0.08</td>
<td>0.44</td>
<td>0.44</td>
<td>-0.21</td>
<td>-0.59</td>
</tr>
<tr>
<td>Mean</td>
<td>0.86</td>
<td>0.09</td>
<td>0.74</td>
<td>0.76</td>
<td>-0.18</td>
<td>-0.29</td>
</tr>
<tr>
<td>SD</td>
<td>0.06</td>
<td>0.05</td>
<td>0.36</td>
<td>0.41</td>
<td>0.06</td>
<td>0.15</td>
</tr>
</tbody>
</table>

* The Max sim and Min sim are the maximum and minimum values of knee joint moments predicted by the PENm. The Max Exp and Min Ex are the maximum and minimum values of experimental knee joint.

6.3.2 Spatiotemporal gait parameters

Spatiotemporal gait parameters such as kinetics, kinematics from hip, knee, and ankle joint in sagittal plane are presented in this section. Mean, standard deviations (SD) and peak values are calculated for kinetic and kinematic results. Spatiotemporal gait parameters from eight gait cycles are presented in Table 6.5.
Table 6.5: Spatiotemporal gait parameters

<table>
<thead>
<tr>
<th>Gait cycle</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cadence</td>
<td>83.3</td>
<td>103</td>
<td>119</td>
<td>114</td>
<td>104</td>
<td>99.2</td>
<td>129</td>
<td>126</td>
<td>110</td>
<td>14.6</td>
</tr>
<tr>
<td>Speed</td>
<td>0.78</td>
<td>0.81</td>
<td>1.08</td>
<td>1.07</td>
<td>0.75</td>
<td>0.82</td>
<td>1.01</td>
<td>1.02</td>
<td>0.92</td>
<td>0.14</td>
</tr>
<tr>
<td>Step width (m)</td>
<td>0.21</td>
<td>0.18</td>
<td>0.05</td>
<td>0.08</td>
<td>0.19</td>
<td>0.13</td>
<td>0.11</td>
<td>0.12</td>
<td>0.14</td>
<td>0.057</td>
</tr>
<tr>
<td>Stride length (m)</td>
<td>1.12</td>
<td>0.95</td>
<td>1.09</td>
<td>1.12</td>
<td>0.86</td>
<td>1</td>
<td>0.94</td>
<td>0.97</td>
<td>1</td>
<td>0.095</td>
</tr>
<tr>
<td>Stride time (s)</td>
<td>1.44</td>
<td>1.17</td>
<td>1.01</td>
<td>1.05</td>
<td>1.15</td>
<td>1.21</td>
<td>0.93</td>
<td>0.95</td>
<td>1.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Double support (%)</td>
<td>22.22</td>
<td>23.1</td>
<td>17.8</td>
<td>18.1</td>
<td>37.4</td>
<td>29.8</td>
<td>16.1</td>
<td>20</td>
<td>23.4</td>
<td>9</td>
</tr>
<tr>
<td>Single support (%)</td>
<td>38.9</td>
<td>47.9</td>
<td>43.6</td>
<td>37.1</td>
<td>34.8</td>
<td>37.2</td>
<td>44.1</td>
<td>36.9</td>
<td>39.7</td>
<td>6.9</td>
</tr>
<tr>
<td>Stance phase (%)</td>
<td>61.1</td>
<td>70.9</td>
<td>61.4</td>
<td>55.2</td>
<td>72.2</td>
<td>66.9</td>
<td>60.2</td>
<td>56.8</td>
<td>63.1</td>
<td>6.27</td>
</tr>
</tbody>
</table>

Table 6.6: Peak angle values and ROM of hip, knee and ankle joints in sagittal plane

<table>
<thead>
<tr>
<th>Joint</th>
<th>CP (degree) Max</th>
<th>Min</th>
<th>ROM</th>
<th>TD (degree) Max</th>
<th>Min</th>
<th>ROM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hip</td>
<td>35.19</td>
<td>-1.95</td>
<td>37.14</td>
<td>30.20</td>
<td>-15.7</td>
<td>45.95</td>
</tr>
<tr>
<td>Knee</td>
<td>61.83</td>
<td>25.70</td>
<td>36.13</td>
<td>59.95</td>
<td>1.64</td>
<td>58.31</td>
</tr>
<tr>
<td>Ankle</td>
<td>14.93</td>
<td>-1.52</td>
<td>16.45</td>
<td>12.00</td>
<td>-19.85</td>
<td>31.85</td>
</tr>
</tbody>
</table>
Figure 6.5: Mean joint angles of hip, knee and ankle joint and the SD during an entire gait cycle in the sagittal plane. Red line: Mean joint angles for CP group. Green line: Mean joint angles for TD group. Red shaded area: SD of joint angles for CP group. Green shaded area: SD for TD group. Units for hip, knee ankle angles are degrees. Positive and negative values for hip angle and knee angle are flexion and extension. Positive and negative values for ankle angle are dorsiflexion and plantarflexion.

Figure 6.5 summarizes mean joint angles of hip, knee and ankle joint from CP subjects and typically developing (TD) subjects in the sagittal plane. Table 6.6 summarizes maximum (Max), minimum (Min) values and the range of motion (ROM) of hip, knee, and ankle joint from both CP subjects and TD children. The reference joint angles of TD children are obtained from Schwartz and Rozumalski’s study [290, 291]. The ROMs of hip, knee and ankle joint (37.14°, 36.13°, 16.45°, respectively) from CP are smaller than those from TD children (45.95°, 58.31°, 31.85°, respectively). Table 6.3 shows that the entire stance phases of CP subjects are different from those of TD subjects (63.1% compared with 60% [5]).
At initial contact, hip joints of CP flex at 35°, compared with those of TD at 30°. During loading response at around 10% gait cycle point, the thigh is relatively stable. During mid-stance and terminal stance (10%-30% and 30%-50% gait cycle), hip joints of CP reach its peak extension position at ~1.95°, compared with those of TD at ~15.7°, which indicates that hip joints from CP subjects have inadequate hip extensions. During pre-swing (50%-63% gait cycle for CP and 50%-60% for TD), initial swing (63%-73% gait cycle for CP and 60%-70% gait cycle for TD) and mid-swing phase (73%-87% gait cycle), hip angles flex to 35° for CP, 30° for TD. Hip flexion angles are maintained in terminal swing phase within 5°.

At initial contact, knee joints flex at about 35° for CP subjects, while for TD subjects knee joints flex at around 3°. During load responding phase, knee joints flex to 40° for CP subjects, while for TD subject knee joints rapidly flex to 20°. During mid-stance, knee joints gradually extend to around 35° for CP subjects, while for TD subjects knee joints extend to around 3°. From terminal stance to mid-swing, knee joints flex rapidly to around 60°. During terminal swing phase, knee extension continues until full extension (35° for CP subjects and 3° for TD subjects) is gained. Then for TD subjects, knee joints drop into minor degrees of flexion, while for CP subjects they do not have such flexion.

During the initial contact, ankle plantar flexes around 3° for TD subjects, and follows the first plantar flexion arc (with the plantar flexion of 10°) during the load response. For CP subjects, ankle starts the gait cycle with a dorsiflexion at around 5° and there is no plantar flexion during load response period. Dorsiflexion continues through mid-stance and the first half of terminal stance, reaching the maximum dorsiflexion (15° for CP and 12° for TD subjects). During the terminal double support (53%-63% for CP, 50%-60% gait cycle for TD), ankle joint plantarflexes to 1.5° for CP subjects, while for TD subjects ankle rapidly plantar flexes to around 20°
at the end of stance. For TD subject, toe-off initiates the final plantar flexion and ankle joint reaches to a neutral position by mid-swing and maintains during the rest of the phase within $5^\circ$ drop of plantar flexion. While for the CP subjects, during mid and terminal swing phase, ankle joint dorsiflexes and maintains at around $8^\circ$ within $5^\circ$ of dorsiflexion.

Figure 6.6: The mean experimental hip, knee and ankle joint moment and standard deviations in sagittal plane. In each sub figure, solid curves are mean values of hip, knee and ankle moment. The shaded areas are mean values plus and minus one standard deviation. Moments are normalized to subjects’ corresponding body weight. Gait cycles are normalized to 100 frames. The units are $Nm/Kg$. Positive and
negative values for hip, knee and ankle moment are: extension and flexion moment for hip and knee joint, plantar flexion and dorsiflexion moment for ankle joint.

Figure 6.6 shows the mean and SD of hip, knee and ankle joint moments. At initial contact, hip joint has an extension moment of 0.18 $Nm/Kg$. Hip extension moment increases to 0.73 $Nm/Kg$ during the middle of load response phase and then decreases to 0.42 $Nm/Kg$ at the end of load response. During the mid-stance, extension moment reaches its second extension peak at 0.61 $Nm/Kg$ and then decreases to zero at 36% gait cycle. Hip joint then is governed by flexion moment until the end of mid-swing phase (87% gait cycle), with the peak flexion moment of 0.56 $Nm/Kg$ at the pre-swing phase. For knee joint, extension moment takes in charge of the movement from load response to pre-swing phase with two extension peaks (0.45 $Nm/Kg$ and 0.48 $Nm/Kg$ at 10% gait cycle and 51% gait cycle, respectively). Flexion moment increases from pre-swing to mid-swing, reaching peak flexion moment of 0.12 $Nm/Kg$ and then the flexion moment gradually decreases and changes to extension moment at the end of the gait cycle. The ankle joint is controlled by plantar flexion moment during the entire stance phase. There are two peaks of plantar flexion. One is 0.75 $Nm/Kg$ at 16% of the gait cycle and the other peak is 0.91 $Nm/Kg$ at 47% of the gait cycle.

6.4 Discussion

6.4.1 The performance of the PENm model for CP patients

Results show that the PENm predicts knee joint moment for CP patients based on EMG signals from one knee extensor and flexor muscle with an acceptable accuracy ($R^2=0.86\pm0.06$). As described in previous research [204, 206, 219], the mean $R^2$ values between the estimated knee joint moments and those calculated via inverse
dynamics are around 0.91. After calibration, the mean calculation time is around 0.02 second. The results show the possibility of employing the PENm to control gait rehabilitation robots for CP patients.

The simulation results provide more in-depth information about the muscle functions for CP patients during crouch gait. As shown in Figure 6.4, the vastus force profile shows two peaks, occurring early and later in the stance phase, respectively. This is an interesting finding. In comparison, for normal gait, the vastus [242] doesn’t have a high activation during late stance phase. A possible explanation is that, crouch gait, as the knee is flexed, requires increasing muscle activation for the knee extensors (vastus and rectus femoris) to maintain the posture. Therefore, the knee extensors generate large amount of forces in the stance phase, which also result in the increase of knee joint loading. As aforementioned, crouch gait may be caused by spasticity in hamstrings and/or weak gastrocnemius and soleus. The EMG profile and simulation results show that hamstring forces are similar to normal walking. The results support that crouch gait is not caused by spasticity in hamstrings for the patients we tested. Therefore, any hamstring tendon transfer surgeries, which are common options for crouch gait treatment, may not be beneficial for these patients.

Although the simulation results can provide in-depth information to understand muscle functions, due to the simplicity of the model (two EMG channels from two knee muscles), the simulation can only provide information for the knee joint. Future work is expected to improve the model by adding more muscles in other joints, e.g. ankle joint.

In addition, the PENm model has a potential application of assessing spasticity level. Currently, modified Ashworth scale is the most widely used method to assess spasticity [293]. The scale is a subjective measurement, which means its reliability highly depends on the experiences of clinicians. Sometimes, it’s difficult to separate
stiffness due to muscle stiffness from the stiffness caused by spasticity [294]. EMG measurement has also been considered as an assessment method. But EMG itself cannot indicate any information about the magnitude of muscle forces. The EMG-driven model developed in this study has the potential to serve as an objective measurement. To achieve this goal, more improvements need to be done. For CP patients with spasticity, their muscles have fewer muscle fibers, shorter fiber length, decreased cross-sectional area, and a longer tendon [294]. To achieve better simulation results, this information needs to be incorporated into the current model by changing some model parameters.

6.4.2 Gait deviations in sagittal plane from the gait analysis information

During level ground walking, compared with TD subjects, CP patients walk with increased knee flexion and ankle dorsiflexion in stance phase. As shown in Figure 6.5, the increased knee flexion and ankle dorsiflexion throughout stance are the characteristics of crouch gait, which indicate the CP children participated in this study may have spasticity in hamstrings and/or weak gastrocnemius and soleus.

For hip joint, CP patients show inadequate extension during mid-stance and terminal stance phase (10%-50% gait cycle). They also show excessive flexion during initial-swing (50%-63% gait cycle) and mid-swing (70%-90% gait cycle). Inadequate hip extension influences the person’s weight-bearing stability and progression. The excessive flexion results in a major limb posture change. For knee joint, CP patients show excessive flexion during load response (10% gait cycle), terminal stance and pre-swing (40%-63%). During mid-stance (10%-40% gait cycle), mid and terminal swing (70%-100%), knee joint has inadequate extension. For ankle joint, CP patients show excessive dorsiflexion during the entire gait cycle except for mid-stance phase.
As illustrated in Figure 6.5, CP patients need generating more ankle moment during the early stance phase by maintaining an award couch posture (excessive ankle dorsiflexion and knee flexion), which add more loads on the ankle and knee joints. A recent biomechanical study shows that the peak knee joint force is greater than six times bodyweight for severe crouch gait [22].

6.5 Summary

This study evaluated the PENm and studied muscle functions for CP patients. The results show that the PENm predicts joint moment based on two EMG channels with an acceptable accuracy. The results also provide in-depth information about muscle functions during crouch gait. In the future, the PENm for cerebral palsy can be employed in gait rehabilitation robots to take into account movement intention of CP patients. The PENm also needs to be improved to provide more comprehensive understanding of the cause-and-effect relationship between muscle functions and abnormal gait.
Conclusions and future work

This chapter summarizes the main research outcomes and conclusion of this thesis, as well as highlight the main contribution made during the Ph.D. study. The chapter also provides a discussion of future research direction to advance the study presented in this thesis.

7.1 Research contribution and conclusion

This thesis presented two neuromusculoskeletal models that were specifically designed for real-time robotic applications. One was the patient-specific muscle force estimation model (PMFE) and the other was the patient-specific EMG-driven neuromuscular model (PENm). These two models estimated patient’s movement intention in real-time and accounted for patient-specific properties. The PMFE was firstly evaluated by gait analysis data from healthy subjects. Development and evaluation of the biological command based controller for a human-inspired gait rehabilitation exoskeleton were presented as one case study of translating patient’s movement intention to robot status and then executing the rehabilitation task. The
PENm was evaluated by gait analysis data including kinematics, kinetics, ground reaction forces, and raw EMG signals of selected muscles from both healthy and cerebral palsy adolescents. The PENm was also proved that it provided more in-depth information about muscle functions in comparison with 3D gait analysis technique. The major outcomes and contribution are summarized in the following sections.

**7.1.1 The patient-specific muscle force estimation model**

As explicitly discussed in Chapter 2 and 3, the existing controllers for rehabilitation robots failed to fulfil the requirement of optimal mental engagement and self-initiative. An optimal controller should be based on the patient’s physiological properties and the patient’s own voluntary movement and intention [51, 52]. Therefore, musculoskeletal models could be incorporated in the controllers of human-inspired gait rehabilitation robots to model the human dynamics more accurately and detect the patient’s intention. A possible solution is controlling the robot by voluntary muscle forces generated by patients based on the patient-specific musculoskeletal model. The non-invasive method, inverse dynamics based static optimization, is successfully employed in biomechanics to estimate individual muscle forces and study muscle functions [179-185]. However, these models cannot be applied in gait rehabilitation robots because they are not able to achieve real-time computation, which motivated this study.

The PMFE developed in this study (Chapter 3) made the following contribution for robotic applications.

- Firstly, the PMFE employed a patient-specific musculoskeletal model tailored for the user to identify accurate anthropometric parameters,
Conclusions and future work

anatomical parameters and muscle moment arms for accurate modelling each patient’s movement dynamics for and accounting for patient variability.

- Secondly, unlike previous inverse dynamic-static optimization model including as many as possible muscles around one joint [179-185], the PMFE simplified the musculoskeletal model by incorporate one extensor muscle and one flexor muscle around knee and hip joint to realize real-time calculation. This simplification was according to human’s muscular mechanism and the actuation system of the human-inspired gait rehabilitation robots.

- Thirdly, to achieve real-time calculation, analytical algorithms, the Lagrange multiplier method, instead of the numerical algorithms, were applied in the static optimization procedure.

Joint moment and the corresponding extensor and flexor muscle forces calculated by the PMFE was compared with those calculated via Inverse Dynamics (ID) tool of OpenSim and computed muscle control (CMC) algorithm. Inverse dynamics and CMC are well-defined approaches to provide realistic estimations of joint moment and muscle forces [81, 186, 231, 239, 242, 243, 245, 252, 254]. Therefore, the hip and knee joint moments calculated via the ID tool of OpenSim and the muscle forces calculated via the CMC tool of OpenSim were regarded as the “ground truth” or “actual value” of the corresponding hip and knee joint moments and muscle forces. The results showed that the PMFE model estimated joint moment and individual muscle forces accurately. The $R^2$ values between hip and knee flexion/extension moment calculated via the PMFE and the ID tool of OpenSim were greater than 0.95 and the averaged RMSE values were 0.04 Nm and 0.022 Nm respectively. Muscle forces calculated via the PMFE and the CMC had good correlations. The averaged $R^2$ values of knee/hip extensor and flexor muscle forces were 0.89. The joint moments and muscle forces predicted by the PMFE were similar to those reported in the literature [5, 181, 183, 195]. Similar to other static optimization models [183,
185, 193, 195], muscle force patterns predicted via the PMFE model were agreeable with muscle activation levels (reflected by EMG signals). Normally it took more than 200 seconds to calculate joint moments and individual muscle forces using ID and CMC tools of OpenSim from kinematics data from one gait cycle [231]. The PMFE, compared with those OpenSim tools, showed great computational efficiency with the mean calculation time is $0.02 \pm 0.003$ s for the entire gait swing phase (about 40% of gait cycle). In summary, the proposed PMFE model has been proved to be a promising method to provide accurate muscle forces as the biological control inputs for rehabilitation robots.

**7.1.2 The biological command based controller**

Task-oriented, repetitive gait training [29-37] is effective for patients with gait dysfunctions after neurological disorders, especially during the acute phase of these diseases. While previous rehabilitation robots guide or assist the patient with repetitive training, they failed to engage the neuromuscular control [34, 46]. One of the major issues of the conventional control design is that they cannot assess the patients’ dysfunctions at muscle level. Most controllers are implemented at joint level by controlling joint torque or joint angle [53-56] through actuators. Although some novel actuators like pneumatic air muscle actuators have been developed to mimic muscle behaviour, the limitation of the conventional control design cannot take the most advantages of these actuators.

This research developed a *patient-specific biological command based controller* (PSBc) to solve this problem (Chapter 4). The controller provided patient-specific, task-oriented, repetitive robotic gait training for acute stage of neurological disorder patients under patient’s intention (desired individual muscle forces under neuromuscular control law [186]), which was predicted by the PMFE model. Furthermore, this controller incorporated accurate patient-specific anthropometric
and anatomical parameters through the patient-specific musculoskeletal model and thus ensured good performance as well as maximum comfort.

The PSBc was based on the patient-specific muscle force estimation model, which calculated desired muscle forces for extensor and flexor of a joint under the neuromuscular control of the subject. The PSBc translated patient’s intention, i.e. the required muscle forces, from the PMFE model to robot command for actuation system control. The PSBc employed the PMFE model in the feedforward control loop to ensure the pneumatic actuators produce desired muscle forces. A close-loop PID controller modeled the error and disturbances of the human-robot system. The PMFE based feedforward controller for each of the pneumatic actuators, improved performance by accurately predicting the exact control requirements and accurately modelling the system.

The PSBc was evaluated by computer simulation and experiments. The computer gait analysis data from six adolescents at three speeds was used in the computer simulation. The results showed that the HuREx had good performance on tracking desired joint angles and muscle forces for all subjects at three speeds. The $R^2$ between desired and actual parameters were greater than 0.97 and the RMSE values were lower than 2.55 degrees at all compliant levels. The experiment showed similar results. The PSBc can accurately track desired joint trajectories and at the same time take into account muscle function and motor control. The $R^2$ values between desired and actual muscle forces were greater than 0.99 and the values for joint angles was greater than 0.87. The position tracking performance of the PSBc was similar with that of a traditional model-based feedforward controller [82, 88] on the HuREx.
7.1.3 The patient-specific EMG-driven neuromuscular model

Chapter 3 and Chapter 4 presented the PMFE and one case study of employing the PMFE to control a human-inspired gait rehabilitation robot. Although the PMFE calculated muscle forces in real-time, it still had the following limitations such as the highly sensitivity to kinematic data, difficulty to solve co-contraction of movement, and neglecting of activation dynamics of muscles. To this matter, this research developed a patient-specific EMG-driven neuromuscular model (PENm) to estimate patient’s movement intention and include subject variability at the same time.

The model had made the following improvements for gait rehabilitation robots by decreasing calculation time and ensuring good prediction accuracy at the same time.

- Firstly, previous EMG-driven models included many muscles around one joint [204] and a lot of adjusting parameters [219] to ensure good joint moment estimation performance. However, this lead to longer calculation time and poor prediction ability for novel data, this research simplified the patient-specific musculoskeletal model to include two antagonistic muscles around one joint and the minimum set of adjusted parameters to ensure robustness of the PENm.

- Secondly, previous models employed separate force-length (FL) and force-velocity (FV) relationships in the contraction dynamics modelling. However, it is not physiological to use FL and FV relationship separately [204, 209, 212, 219]. This research employed combined FLV relationship in muscle mechanics, which modelled muscle contraction dynamics more accurate and thus predicted more reliable muscle forces from raw EMG signals.

- Thirdly, the pervious iterative algorithms such as Runge-Kutta-Fehlberg algorithm failed to realize real-time calculation. This research developed a
dynamic computational model for real-time calculation [204, 205, 207, 209, 212].

- Fourthly, previous EMG-driven models failed to consider subject variability. They used generic [204] or non-anatomical musculoskeletal models [218, 219]. While, the PENm was based on the patient-specific musculoskeletal model, which modeled the PENm accurately with patient-specific musculotendon parameters (such as the optimal muscle fiber length, the maximum isometric force, and tendon slack length) and muscle kinematics (musculotendon length and muscle moment arms) during static and dynamic poses.

This research also conducted a sensitivity analysis on the musculotendon parameters to find out a minimum set of parameters. Eight muscles around knee joint were investigated, which are *rectus femoris* (RF), *vastus intermedius* (VI), *vastus lateralis* (VL), *vastus medialis* (VM), *biceps femoris caput longum* (BFL), *biceps femoris caput breve* (BFS), *semitendinosus* (SM), and *semitendinosus* (ST). Parameters with higher sensitivity require greater accuracy in the PENm. The sensitivity analysis was based on gait analysis data from a previous study [250], including kinematics, ground reaction forces and raw EMG signals from six healthy adolescents. The results of the sensitivity analysis showed that knee joint moment during gait has a high or medium sensitivity to only a few of musculotendon parameters. The knee joint moment was found to be highly sensitive to tendon slack length, optimal muscle fibre length and maximum isometric force, which was similar with studies from literature [279, 295-298]. Moreover, this research also investigated the sensitivity of knee joint moment to the model inputs (such as musculotendon length, muscle activation and muscle moment arms) and found that knee joint moment was highly sensitive to those model inputs.
By comparing the knee joint moment calculated via the PENm and the experimental joint moment, the PENm has proved that it estimates knee joint moment accurately at all three speeds (low, free and fast) in real-time by using only EMG signals from one knee extensor and one knee flexor. The correlation coefficients between the simulation results and the experimental reference were greater than 0.91, which was an acceptable accuracy when comparing with results from other researchers [204, 206, 219]. As described in previous research [204, 206, 209, 219], the mean R² values between the estimated knee joint moments and those calculated via inverse dynamics were around 0.91. For previous models [204, 206, 209, 219], it took at least several minutes to predict joint moments from EMG signals depending on the different complexity of musculoskeletal models they used. While the calculation time for the PENm was 0.025 ± 0.003 seconds. The results demonstrated that the PENm model provided a solution to incorporate patient’s movement intention in gait rehabilitation robots.

7.1.4 The patient-specific EMG-driven neuromuscular model for clinical populations

Besides its application for rehabilitation robots, the PENm model can also be used as a quantitative functional assessment tool for patients with neurological disorders. For cerebral palsy patients, the PENm model can help to identify abnormally functioning muscles and predict treatment outcome. The simulation results can provide in-depth information about the muscle function for CP patients by knowing muscle forces during movement.

This study conducted gait analysis experiment on cerebral palsy (CP) patients to record the gait analysis data including kinematics, kinetic and raw EMG signals from selected muscles (see Chapter 6). By comparing the knee joint moment via the PENm for CP patients and the experimental joint moment, the PENm was proved
that it estimated knee joint moment accurately. The mean $R^2$ and RMSE values between the knee joint moment and the experimental reference are $0.86 \pm 0.06$ and $0.09 \pm 0.05 \text{Nm/Kg}$. Furthermore, compared with mean $R^2$ values reported in the literature [204, 206, 209, 219], in which the $R^2$ values are around 0.91, the PENm predicted knee joint moment accurately for cerebral palsy patients. Flexor and extensor muscle forces prediction ability of the PENm was evaluated via against raw EMG signals, which reflects muscle activations. The highly agreeable patterns between these two show the good muscle force estimation performance of the PENm for cerebral palsy patients.

The simulation results provide more in-depth information about the muscle function for cerebral palsy patients by knowing muscle forces during movement. Moreover, the PENm for CP patients is able to assess the spasticity level. The most widely used method of spasticity assessment, the modified Ashworth Scale [299], is limited in several aspects. The reliability of the model highly depends on experiences of the clinicians and it is difficult to separate muscle stiffness from the stiffness caused by spasticity [300]. The PENm model can be used as an objective measurement to indicate information about the muscle spasticity levels.

### 7.2 Publications Arising from this Thesis

The following papers have been published or in press in peer-reviewed journals or conference proceedings:


- **Ye Ma**, Shengquan Xie, Yanxin Zhang, A patient-specific EMG-driven neuromuscular model for the potential use of human-inspired gait


### 7.3 Future work

In the area of gait rehabilitation robots, the author will further improve the effectiveness of rehabilitation robots.

Firstly, a patient-specific human-robot cooperative controller for gait rehabilitation will be developed based on the proposed PMFE model and the EMG-driven neuromuscular model. Different from the PSBc designed for acute rehabilitation, the patient-specific cooperative controller is designed for gait rehabilitation in chronic phase. Utilising the feedback information from EMG-driven models, the patient-specific human-robot cooperative controller will provide assistant as necessary as
needed for gait disordered patients. Patients are encouraged to walk voluntarily, not only follow desired muscle forces patterns.

Secondly, the effectiveness of the proposed neuromusculoskeletal models and the patient-specific human-robot cooperative controller will be evaluated by experiments with patients performing gait rehabilitation training. The temporal-spatial parameters, kinematic and kinetic properties, muscle functions will be compared. The research question is that whether the robot-aided rehabilitation can improve active participation of the patients compared with the conventional robot-in-charge controller and the human-robot cooperative controller.

Thirdly, applications of the proposed models and techniques will be explored in other circumstances such as elbow joint rehabilitation, hip joint rehabilitation or ankle joint rehabilitation. The parameters of the neuromusculoskeletal models need to be optimized or tuned for those different circumstances. The rehabilitation training is all important for post-neurological disorder patients to regain motor ability of actively daily living and thus will greatly improve their quality of life. These techniques are also helpful for the development of artificial limbs for amputee. A lot of artificial limbs these days are passive and did not take into account patients’ musculoskeletal system, let alone patient’s movement intention and motor control. Our neuromuscuoskeletal models will help to build intelligent artificial limbs by the patient-specific musculoskeletal system, taking into account patient’s intention via EMG signals from residual limbs.

In the area of gait analysis and assessment, the future work will start from the patient-specific EMG-driven neuromuscular model. The author will work on building a complex patient-specific EMG-driven neuromuscular model to investigate muscle functions and gait assessment in addition to gait analysis techniques.
The modified complex patient-specific EMG-driven neuromuscular model will include more muscles around the knee joint. Besides, force-length-velocity relationships in the contraction dynamics of the EMG-driven models will be investigated and compared. The author will work on developing a patient-specific EMG-driven neuromuscular model for different patients by adjusting model parameters accounting for the amount of muscle fibers, muscle fiber length, the cross-sectional area of muscles or tendon length.

The complex EMG-driven neuromuscular model has the potential to evaluate muscle functions for patients with gait disorders or other clinical applications more accurately. The model could give more insight information of the gait dysfunction in addition to the traditional gait analysis technique. For neurological disorder patients with spasticity, their muscles have fewer muscle fibers, shorter fiber length, decreased cross-sectional area, and a longer tendon [294]. To achieve better simulation results, this information needs to be incorporated into the current model by optimizing model parameters.


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