Individual-specific gait pattern planning and locomotion control strategy for robotic gait rehabilitation

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2014

Luu, T. P. (2014). Individual-specific gait pattern planning and locomotion control strategy for robotic gait rehabilitation. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/58912>

<https://doi.org/10.32657/10356/58912>

INDIVIDUAL-SPECIFIC GAIT PATTERN PLANNING AND LOCOMOTION CONTROL STRATEGY FOR ROBOTIC GAIT REHABILITATION

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A thesis submitted to the Nanyang Technological University

in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

2013

Abstract

Spinal cord injury (SCI) and stroke are the leading cause of permanent disability around the world. Majority of these patients has to go through gait rehabilitation to regain their walking ability. The objectives of this research work are to introduce an individual-specific gait pattern prediction model and to design a *subject-cooperative* control strategy for robotic gait rehabilitation to improve the therapeutic outcomes.

Robotics is gaining its popularity in gait rehabilitation. Gait pattern planning is important to ensure that the gait patterns induced by robotic systems are tailored to each individual and varying walking speed. Most research groups planned gait patterns for their robotic systems based on Clinical Gait Analysis (CGA). The major problem with CGA data is that it cannot accommodate inter-subject differences and it is limited to only one walking speed as per the published data. In this work, an individual-specific gait pattern planning model was developed to generate walking gait patterns based on gait parameters (stride length, cadence) and anthropometric data of targeted subjects. The results showed that the proposed model was able to generate gait pattern better than CGA approach in term of resembling the actual gait pattern of the targeted subject.

Reviews on locomotor control in robotic gait rehabilitation showed that passive training strategy does not provide an ideal training for patients who have capability of some voluntary motor control. If patients are trained with totally passive training strategy, they tend to train with reduced activity of muscles and metabolism. This work introduces a gait pattern adaptation model for *subject-cooperative* control strategy in robotic rehabilitation. Based on the human-machine interaction, the walking speed is updated and gait pattern is modified during the training process. This model allows the subject to interact with the machine and increase their effort in the training session.

This thesis presents a new robotic assisted gait rehabilitation methodology. The methodology is accompanied with the human gait locomotion study, development of a control module hardware for an over-ground gait trainer, motion planning for natural gait-like implemented on robotic assisted systems and design of *subject-cooperative* locomotion control strategy.

Acknowledgement

This is a great opportunity for the author to express his deep gratitude to his supervisors, Professor Low Kin Huat and Professor Qu Xingda for their guidance, support and encouragement during the first two years of the author's candidature period. The progress of this research work would not have been smooth without their necessary assistance, trenchant critiques and precious advices.

The author is also pleased to thank Mr. Lim Eng Cheng, Ms. Agnes Tan and Mr. You Kim San from the Robotic Research Center (RRC) for their willingness to support the author to manage the machines and equipment in the laboratory, to collaborate with the suppliers and to facilitate the administrative procedure. The support and facilities from Motion Capture Laboratory and the Center for Human Factor & Ergonomics are also acknowledged. The author also would like to thank all the lecturers and professors in NTU for providing the author basic knowledge in engineering and research field.

A heartfelt gratitude is given to Mr. Lim Hup Boon for his experience sharing during the first stage of the author's research period. A special thank you also goes out to the research group for their kindness to share knowledge and valuable advices, Mr. Zhou Chunlin, and Mr. Li Lei. The assistance from project officers, Mr. Lei WenKang and Mr. Tan Elton; and from the FYP students, Mr. Narendra Utama, Mr. Lim Sze Jie, Mr. Lim Jun Jie, Mr. Aung Thu Myint, Mr. Tan Wei Qin, Mr. Lim Kok Siang, and Mr. Jeffrey Wang are also acknowledged.

It is an honor for the author to give a special thank to the Department of the Rehabilitation Medicine at the Tan Tock Seng Hospital (TTSH) and the equipment and financial supports provided by the NMRC Research Grant 1051/2006. The author would like to thank Mr. Neo for his participation in clinical trial. Participants in motion capture and *NaTure-gaits* experiments are also acknowledged.

Last but not least, the author remains indebted to his family and all of his friends for their encouragement and advices which help the author to overcome unexpected difficulties during the time staying oversea.

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Chapter 1

INTRODUCTION

1.1 Background

Spinal cord injury (SCI) and stroke are the leading cause of permanent disability around the world. In the United States, approximately 795,000 people have a new or recurrent stroke annually[1], and an estimated 232,000 to 316,000 persons live with SCI[2]. Loss of walking ability is a debilitating outcome in post-stroke and spinal cord injury, with more than 50% of the post-stroke patients demonstrating persistent walking deficits, and more than 90% of the SCI patients lose their sensory and motor control of the lower limbs. Majority of these patients have to go through gait rehabilitation in order to regain the ability of independent walking.

For many years, the conventional rehabilitation method such as passive stretching [3], acupuncture, or general home exercise [4] has been focused on promoting the maximum capacity of strength and endurance in muscles. This method can be voluntarily activated after injury and teach patients how to use their remaining muscles more effectively with the aid of devices such as clutch, wheelchair ambulation, walker ambulation, etc. This method is also referred as compensation model in rehabilitation and has an assumption that the Central Nervous System (CNS) cannot be recovered after lesion. Some examples of using the traditional method are illustrated in Figure 1-1(a).

On the other hand, the modern rehabilitation method or recovery model is recently inspired by the principle of neuroplasticity. Neuroplasticity allows the neurons in the brain to compensate for injury and disease and to adjust their activities in response to new situations or to changes in their environment. Therefore, it is possible that with appropriate rehabilitation methods and processes, neuronal circuits of stroke patients that have been affected by brain lesion can potentially be retrained, resulting in improving motor control. Unaffected regions of the brain which normally control the contra lateral or synergistic muscles may be trained to take over the control of the affected muscles. The benefits from intensive motor training for stroke patients are demonstrated in [5-9].

For those who are suffering from SCI or stroke, ambulation is the major concern for them. With the conventional rehabilitation method, using wheelchairs can aid mobility and some patients are likely to opt for the use of wheelchair rather than using their ambulation skills after rehabilitation [10]. However, using the wheelchair will cause some constraints for the patients [11]. For example, many in-house and public facilities are designed for bipedal walking and will be big obstacles for wheelchair users. On the other hand, modern rehabilitation method will not only address this issue but also provide the patients with psychological benefit.

Body weight supported (BWS) gait rehabilitation is a modern gait rehabilitation strategy, which was introduced by Barbeau *et al* about two decades ago [12]. The strategy was proposed based on the recovery model of rehabilitation. Conventionally, BWS gait rehabilitation is carried out by suspending patient over a treadmill using cable-harness apparatus. The cable-harness system offload partial of the patient's body weight (hence the training method named BWS). The offloading of the patient's body weight facilitates walking training. With the help of several therapists, the patients' pelvis and lower limbs are guided to complete the gait locomotion. Gait rehabilitation with BWS Therapist Assistance is shown in Figure 1-1(b).

Figure 1-1: Clinical gait rehabilitation (a) Physical rehabilitation with compensation model [13] (b) Body Weight Support with Therapist Assistant (TABWS)[14]

Over the last 10 years, studies have shown that SCI and stroke patients experienced TABWS treadmill training demonstrated improvement in EMG activation patterns and functional locomotor outcomes. The increment in weight

bearing on their legs was also noticeable. The review of the evidences can be found in [15, 16].

However, shortage of therapist manpower, training duration and constant afferent input for the locomotor center are some limitations for TABWS gait rehabilitation method. This method usually requires at least three therapists during the training process. The training session period is usually limited because the required tasks from the therapist such as moving patients' legs and pelvis support can be considered as ergonomically unfavourable and labor intensive. Other problems are that each therapist may provide assistance to patient's legs differently for individual practice and that the performance of a single therapist may even differ from day to day.

To overcome these deficiencies, robotic gait rehabilitation training method has been developed and it has gained extensive attentions from researchers and clinical practitioners in recent years [17]. Several robotic assisted devices such as The Lokomat (Hocoma AG, Switzerland) [18], the Gait Trainer (RehaStim, Germany) [19], KineAssist (Kinea Design, USA) [20], etc have been in clinical use for several years. These automated gait trainers reduce the number of therapists involved. They can also move patient's legs in a reproducible, rhythmical and consistent manner in a longer training session.

1.2 Motivation of Research

Locomotor training requires appropriate sensory inputs to maximize functional recovery [21]. Specificity is one of the major principles of gait rehabilitation [22], which suggests that it is crucial to induce a gait pattern that resembles natural gait pattern of the specific targeted subject during gait rehabilitation. In the context of practicing correct kinematic gait patterns in a repetitive manner, little attention has been diverted to the study of gait pattern used in various gait rehabilitation systems. In manual assisted BWS treadmill gait rehabilitation, the therapist moves the patient leg and pelvic using visual feedback and "feel". The assistance provided can vary greatly between therapists and between training sessions [23].

In comparison, robotic orthosis found in gait rehabilitation systems adopt simplified approach to replicate the leg kinematics [18, 24]. Existing research mainly used Clinical Gait Analysis (CGA) data as the reference in their gait pattern planning [18, 25-28]. Normative gait data from Winter [29] is a reliable and popular resource

of CGA. Gait patterns in CGA database can be easily used for trajectory generation for robotic gait rehabilitation systems. However, gait data in the CGA database were available only for certain individuals. Thus, the CGA data cannot well account for inter-individual differences. Furthermore, CGA data is limited to one recorded walking speed for each individual, and thus cannot allow the changing of walking speed in gait pattern planning.

Originally, robotic rehabilitation devices only moved the patient along predefined trajectories and did not adapt their movements to the activity of the patient. If patients are trained with totally passive training strategy, they tend to train with reduced activity of muscles and metabolism. For example, people with SCI who walk in a robotic gait training device with position control consumed 60% less energy than in traditional manually assisted therapy [30]. On the other hand, if patients try to walk actively while the robotic rehabilitation device remains passively supported, they will work against the resistance of the device, which result in abnormal muscle activity patterns [31].

To address those limitations mentioned above, *subject-cooperative* control strategies are being developed by many research groups [26, 27, 32-43]. These control strategies are expected to stimulate active participation and increase the motivation for the patients. It is hypothesized that *subject-cooperative* control strategies will maximize the therapeutic outcome. The ideal control strategy will do the same as an experienced therapist, it will assist the patient's movement only as much as needed and encourage the patient how to use voluntary muscle efforts and motion strategy [44].

This research work is motivated to develop a gait pattern adaptation control based on gait pattern adjustment model for *subject-cooperative* control strategy. First, an individual-specific gait pattern prediction model is developed to generate walking gait patterns based on gait parameters (stride length, cadence) and anthropometric data of any target subject. Subsequently, gait pattern adaptation control based on gait pattern adjustment model is designed to encourage the patient to maintain a high degree of participation and involvement.

1.3 Objectives and Scope

This research work aims to develop an individual-specific gait pattern planning model and a gait pattern adaptation control strategy for robotic gait rehabilitation.

To achieve the objectives mentioned previously, the scopes of this research work will cover four main areas: 1) developing individual-specific gait pattern prediction model, 2) Design a control system for an existing over-ground gait trainer: *NaTure-gaits*, 3) designing gait pattern adaptation control strategy and 4) biofeedback.

1.3.1 An Individual-specific Gait Pattern Planning Model (*GaitGen*)

- Design a basic gait parameter prediction model that is able to generate self-selected slow or normal walking speed and the corresponding gait parameters of any individual given his/her anthropometric data.
- Study of human gait motion via motion capture system in both time domain and frequency domain.
- Develop an individual-specific gait pattern prediction model that is able to generate walking gait patterns based on gait parameters (stride length, cadence) and anthropometric data of any target subject.

1.3.2 Design of a Controller System for an Existing Over-ground Gait Trainer

• *NaTure-gaits* is an existing over-ground gait trainer developed by Nanyang Technological University (NTU). The robotic system was designed from clinical approach for the provision of the key features of lower limb assistance, pelvic movement assistance, and body weight support in the context of over-ground walking. In this research work, it is utilized for the implementation of the proposed gait pattern adaptation control strategy.

- A control system for *NaTure-gaits* is currently missing. In this work, it is developed to control a total of 14 motors of the *NaTure-gaits*.

1.3.3 A Gait Pattern Adaptation Control Strategy

- *High level controller*: Design a control strategy which adapts walking speed and modify walking gait pattern based on the feedback of human-machine interaction. The gait pattern adaptation control module maintains natural gait-like pattern and proper heel contact. The high level control strategy plans the motion for both robotic orthosis and pelvis mechanism.

- *Low level controller*: Design a position control to send command to the gait rehabilitation system's controllers.

1.3.4 **Biofeedback**

- Kinematic and kinetic data are measured in real time and display to therapists and patients. The information will help the therapists evaluate the therapeutic process and motivate the patients to make effort during the training course.

- Human subject trials are carried out for healthy subjects. Biofeedback data is analyzed and gait assessment tools are applied to evaluate the effectiveness of the proposed control strategy.

Chapter 2

REVIEW ON CLINICAL AND ENGINEERING ASPECTS OF GAIT REHABILITATION

2.1 Clinical Aspects of Gait Rehabilitation

The World Health Organization (WHO) has defined rehabilitation as a progressive, dynamic, goal-oriented and often time-limited process, which enables an individual with an impairment to identify and reach his/her optimal mental, physical, cognitive and social functional level. Gait rehabilitation helps the patients to regain or enhance muscle strength, balance, coordination, endurance, locomotion, correct walking posture and functional mobility activities of daily living (ADL). The principle of gait rehabilitation and the development of gait rehabilitation from manually support to automatic devices are briefly introduced in Figure 2-1.

2.1.1 Three Principles of Rehabilitation

There are three major principles for gait rehabilitation: practice, specificity and effort [10, 22, 45]. When all other things are kept to be equal, more learning will occur with more practicing [46]. Greater intensive of leg rehabilitation improves functional recovery and health related function status. The results were shown by Kwakkel *et al* [47]. Specificity is the second principle of motor learning. In order to improve the performance of a motor task, the best way is to execute that specific motor task again and again [48]. The importance of specificity principle in gait rehabilitation has been highlighted in [21]. Effort is the third principle which indicates that individuals need to maintain a high degree of participation and involvement to facilitate motor learning [49, 50]. The three principles can be considered as a guideline to plan a gait training procedure and design a supporting device for gait rehabilitation.

Figure 2-1: Introduction of gait rehabilitation

2.1.2 Traditional Models of Rehabilitation and Modern Model of Rehabilitation

The aim of traditional model rehabilitation is to promote the maximum capacity of strength and endurance in muscles that still can be voluntarily activated after injury. Since this model assumes that the Central Nervous System (CNS) cannot be recovered after lesion, it compensates for non-remediable deficits of paralysis, weakness and balance by using parallel bars, standing, frames, tilt tables, and other assistive devices. New ambulation skills such as walking with clutches, wheelchair ambulation, walker ambulation, etc are taught by using this model.

On the other hand, the modern model of rehabilitation is inspired by the principle of neuroplasticity. Neuroplasticity allows the neurons in the brain to compensate for injury and disease and to adjust their activities in response to new situations or to changes in their environment. This study does not focus on how neuroplasticity work, additional information on neuroplasticity can be found in reference [51].

Dietz *et al*[52] and Nicol *et al*[53] have published that spinal cords have their own locomotion pattern generators, which are capable of inducing basic gait motion patterns when fed with necessary sensory inputs. It is hypothesized that the pattern generators can be activated, even if there is no voluntary control of these motor segments. Several researches on animals have shown that a spinalized animal can be trained to step again [54, 55]. For stroke or spinal cord injury patients, it has been demonstrated that locomotor training in different forms could be more powerful than conventional treatment using more traditional concepts [21, 56].

2.2 Engineering Aspects of Gait Rehabilitation

2.2.1 Therapist Assisted Body Weight Supported Treadmill Training (TABWS)

Body weight supported (BWS) treadmill training has been successfully applied in gait rehabilitation for patients who has neurological gait disorders after stroke [57] or incomplete spinal cord injury (iSCI). The method of suspending a patient over a treadmill for gait rehabilitation was first reported by Barbeau *et al.* in 1987 [12]. This method was developed based on the observation of spinalized cats that could be trained to walk on a treadmill with partial unweighting of their hindlimbs[54, 55]. Several studies have demonstrated that BWS treadmill training can improve walking in patients with SCI [58-62]. It has been found out that 80% of wheelchair-bounded patients with chronic SCI gained functional walking ability after training [58, 63, 64].

Typically, Therapist Assist Body Weight Supported Therapist Assist (TABWS) gait rehabilitation is carried out by putting modified parachute harnesses on neurologically impaired subjects. The stepping motion on a treadmill is manually assisted by therapists, while body weight of the patient is unloaded by the parachute harnesses. The level of body weight support is adjusted to the maximum sustainable load of the patient, without the buckling of the knee during stance phase. To carry out the stepping training, one therapist is required for each leg. One hand of the therapist will be placed at the anterior surface of the leg, just below the patella. The other hand

will be placed on either foot or ankle to assist the toe clearance during the swing phase as well as heel strike during the beginning of stance phase. The third therapist will be maintaining the trunk of the patient in an upright position by stabilizing the pelvis. The TABWS method was previously illustrated in Figure 1.1.

The benefits of BWS treadmill training are demonstrated. However, if we consider BWS treadmill training in the view of the three principle of gait rehabilitation presented earlier, we can see that this method still has some limitation. First of all, two or more therapists are required to assist with leg motion and stabilize the torso during the training process. These tasks are laborious and the amount of training is often limited by the endurance of the trainers. Therefore, the first principle, practice, is not fully achieved in BWS treadmill training method. Secondly, there are some restrictions when addressing the second principle, specificity. In most BWS treadmill training paradigms, locomotor tasks such as starting, stopping, turning and avoiding obstacles are not supported. The third principle, effort, depends on the parameters chosen by the therapist. The patient cooperative level in TABWS can be measured via the two main parameters: body weight support level and treadmill speed. Some other variables which play an important role in giving biofeedback values for visual display and patient's effort evaluation, such as lower limb angles, ground reaction force, EMG, etc are missing. Measuring the patient's effort is the crucial step in Assist As Needed control strategy to achieve the second principle of gait rehabilitation that BWSTA is not be able to fully satisfy.

2.2.2 Three Principles of Gait Rehabilitation and Robotic Gait Trainers

The three principles of gait rehabilitation are used to verify and justify the effectiveness of robotic gait rehabilitation systems, with the Therapist Assisted Body Weight Supported Treadmill Training (TABWS) used as the benchmark. In term of practice, robotic systems allow longer practice duration compared to therapist assisted body weight support gait rehabilitation.

In view of specificity, the three elements of gait training are used as the criteria for comparison. Robotic system is capable of executing any pre-defined trajectories precisely. Thus, the gait locomotion is able to be induced by robotic system precisely on the patient. In contrast, the gait locomotion provided by therapist has significant deviation [23], which is deemed as poorly controlled in this review. Pelvic motion is

deemed as limited control for robotic systems, due to the constraint of the pelvic motion by the body weight support apparatus. Body weight shifting is only available on therapist assisted body weight supported gait rehabilitation. Both approaches use the similar progression method.

*: Limited systems offer complete over ground walking

[#]: Research on active participation started, however, it is still in research phase

Figure 2-2: Comparisons of therapist and robotic assisted body weight supported gait rehabilitation for three principles of gait rehabilitation

The major weakness of robotic system is the lack of interaction with patient. Patient can remain totally passive during the process of rehabilitation. This greatly reduced the effort of participation of the patient. In comparison, therapist can feel the patient and encourage the patient to participate in the process of rehabilitation. This is the major advantage of therapist assisted body weight supported gait rehabilitation. Though active participation is being researched intensively in those robotic systems, the therapist input for this segment can be hardly replaced [65].

In general, robotic systems show more advantages than therapist assisted body weight supported gait rehabilitation. The robotic system will be even better, if the active participation for robotic system has significant breakthrough. The key points of the comparison are illustrated in Figure 2-2.

2.3 State of the Art of Robotic Gait Rehabilitation Devices

BWS treadmill training is strenuous and physically demanding for therapists; thus, this method is usually limited by personnel shortage and fatigue of the therapists. Several researches have indicated to address the issue of manpower shortage [66]. Secondly, it is labor-intensive to stabilize the trunk of patient and highly difficult to insist on a repeatable walking cycle manually [67]. Therefore, robotic devices are required to address these deficiencies.

In the view of the three principle of rehabilitation, the application of robotic devices enable therapists to carry out effective and automated gait exercises to stimulate recovery of human motor control. In other words, compared to therapist assistant BWS treadmill training, robotic devices help to achieve the first two principles easier [6].

Based on the progression method, robotic assisted gait rehabilitation can be divided into three main groups: BWS treadmill training based, footplate based and over ground walking based. The following section introduces the three groups of robotic assisted gait rehabilitation in term of mechanical design.

2.3.1 BWS Treadmill Training Gait Rehabilitation Systems

2.3.1.1 Lokomat

Lokomat is a robotic gait rehabilitation system developed and distributed by Hocoma AG, Switzerland [68]. Studies have been shown that Lokomat is effective in improving the walking ability of individuals with incomplete spinal cord injury [69, 70]. It is the first commercialized product of robotic assisted BWS treadmill training system first introduced in 2000. Lokomat comes with four modules: body weight offloading, robotic orthosis, computer system, and treadmill.

Patient's body weight is partially supported by the harness-counterweight system. This system consists of a dynamic low inertia suspension module, allows a precise unloading of the patient. The weight of the robotic orthosis is taken care of by spring-loaded counterweight module. Operation of Lokomat is illustrated in Figure 2-3(a).

One of the distinct limitations with the Lokomat is the restriction from the harness placed on the user's trunk and pelvis. This limitation is mainly caused by the approach of body weight support. Lokomat firmly compresses the participant's pelvis in the frontal plane just above the greater trochanters, with sagittal plane restraints using a posterior pad with adjustable straps. As such, during walking with the robotic device, pelvis movement is restricted. These restrictions prevent pelvic rotation and body weight shifting, which then translate to limited movement of the trunk [72, 73]. Due to the limitations of the robotic systems, the movement of pelvis is altered and it is no longer physiologically resembled to movement of pelvis during normal walking.

2.3.1.2 *Active Leg Exoskeleton (ALEX)*

ALEX is developed in University of Delaware, Newark [27] which focuses on the assist-as-needed paradigm for rehabilitation. Overall of this motorized orthosis and its components are shown in Figure 2-4 and Figure 2-5, respectively. ALEX contains four main modules: walker, orthosis, computer system and treadmill.

The first module of ALEX is Walker which supports the weight of the device. The trunk of the orthosis is connected to the walker and it has three degrees of freedom (DoFs). The three DoFs are vertical translation, lateral translation and the rotation about vertical axis. A hip brace is used to secure the human trunk to the trunk of the orthosis.

Figure 2-4: Experiment set up with ALEX on right leg of a subject walking on the treadmill [27]

Figure 2-5: ALEX with a human subject. Major components are labeled[27]

Thigh segment of the orthosis has two DoFs with respect to trunk of the orthosis, one DoF allows the thigh for abduction-adduction in frontal plane and the other one allows the thigh for flexion-extension in sagittal plane. The thigh segment is telescopic that can be adjusted to match the thigh length of the subject. Shank segment of the orthosis has one DoF respect to thigh segment of the orthosis for moving the shank in sagittal plane. Shank segment is also telescopic. Foot segment of the orthosis is a shoe insert which is attached to the shank and has one DoF (plantar/dorsi-flexion). Only hip joint in the sagittal plane and the knee joint are actuated using linear actuators. All other DoFs are passively held with springs.

2.3.1.3 Lower Extremity Powered Exoskeleton (LOPES)

Lower Extremity Powered Exoskeleton (LOPES) is developed in University of Twente, The Netherlands [74]. This device consists of a cable driven exoskeleton for the lower limb and an end effector robot for the pelvis. LOPES has a total number of eight actuated DoFs, two for the horizontal pelvis translation and three rotational joints per leg. One DoF which allows the vertical motion of the pelvis is passively weight compensated by a spring mechanism. Figure 2-6 shows the prototype of LOPES and how a person is connected to this device. Figure 2-7 shows the DoF of LOPES gait rehabilitation robot.

Figure 2-6: (a) Prototype of LOPES. (b) A person is connected to device. [74]

Figure 2-7: DoFs of the pelvis and leg segments of LOPES. (1) forward linear guide, (2) sideways linear guide, (3) parallelogram for vertical motion, (4) hip frontal rotation, (5) hip sagittal rotation, and (6) knee sagittal rotation.[74]

2.3.1.4 PAM and POGO

PAM (pelvic assist manipulator) and POGO (pneumatically operated gait orthosis) are two devices developed by University of California, USA. PAM assists the pelvic motion during stepping using BWS treadmill, and POGO is designed as an

attachment to PAM. PAM provides a five DoFs actuation (actuated by pneumatic cylinder) to the pelvis, the only missing DoF is pelvic tilt. POGO provides assistance for the leg swing by actuating the hip and knee joint in sagittal plane [75]. The BWS module in conjunction with PAM and POGO is the overheard BWS system developed by RobomedicaInc[76]. Figure 2-8 shows how a person is connect to the device and the five DoFs available in PAM.

Figure 2-8: (a) Trainers help to secure patients on the BWS system attached to a treadmill. (b) PAM and POGO in operation. (c) Five DoFs of PAM: forward-backward (x), side to side (y), up and down (z) and pelvic rotation(θ) and obliquity (ϕ)[75]

2.3.2 Footplate Based Gait Rehabilitation Systems

2.3.2.1 HapticWalker

HapticWalker is developed by Charite University Hospital, Berlin, Germany in collaboration with the Technical University of Berlin, Germany [77]. The feet of the patient are attached to the footplates, as shown in Figure 2-9 (b). The training motion is induced to the patient through the two footplates. Each footplate is connected to end effector of a three DoFs robotic arm. The robot arm moves the footplate linearly in the sagittal plane and rotates the foot plate with respect to the axis perpendicular to the

sagittal plane. A photo showing the entire structure of HapticWalker is available in Figure 2-9(a).

The main advantage of HapticWalker is that the training profile is not limited to over ground walking. While the machine is able to provide arbitrary foot trajectories training, the trajectories is altered due to the limited movement of the pelvic. However, the motion outcome of hip and knee joints is questionable, since controlling ankle trajectory alone resulted in multiple possible motion outcomes for hip and knee joints.

Figure 2-9:(a) HapticWalker[78]; (b) Foot binding on the footplate [79]

2.3.2.2 *GT-II*

The floor area requirement of HapticWalker is relatively larger than any other available robotic gait rehabilitation systems. For this reason, Gait Trainer I (GT I) is developed as a simplified version of HapticWalker. GT I provides fixed foot trajectory of walking based on the footplate principle [80]. The motion is achieved by a double crank and rocker gear system. Figure 2-10 shows the GT I with patient and the functional principle of the machine.

Figure 2-10: (a) GT-I with stroke patient, (b) Functional principle of the machine[80]

2.3.3 Overground Walking Based Gait Rehabilitation Systems

2.3.3.1 Walk Trainer

The WalkTrainer (WalkTrainer™ is a commercial trademark of the Swiss Foundation of Cyberthosis) is composed of deambulator, BWS, pelvic orthosis, and leg orthoses[25].

The deambulator is the mobile frame of WalkTrainer, which follow the patient during the exercise. Deambulator is designed to carries all the sub-components. Two motorized wheels are equipped in a different way allow motion along the forward axis and a rotation around the vertical axis. The primary function of BWS is the unloading of the user by a certain amount of force. The unloading force is taken care of by a preloading spring, a DC motor is used to compensate for small disturbances which are monitored by a force sensor. The pelvic orthosis is an Artigue parallel structure, provides six actuated DoFs to assist the pelvic motion. The leg orthosis provides motion assistance to the thigh, shank, and foot in the sagittal plane. The overall concept of WalkTrainer is illustrated in Figure 2-11.

Figure 2-11: WalkTrainer™ concept and its prototype [25]

2.3.3.2 KineAssist

KineAssist is a robotic device for gait and balance training developed by Chicago PT LLC (renamed to Kinea Design, LLC) [20]. The main objective of this device is to assist clinicians in maintaining patient safety, while the patient is performing walking, and balancing exercises. The photo of KineAssist in operation is shown in Figure 2-12.

KineAssist consists of an omni-directional mobile base, which was developed based on Cobot Technology. The mobile platform provides forward and turning motion in order to follow the subject, and to turn around corners. Motion intention of the patient is detected by a combination of passive sliders and integrated force sensors, which are incorporated into the body weight support structure at the pelvic part of the patient. KineAssist can support a patient's weight of up to 150 pounds in the vertical direction. The support force is provided by vertical column, which is powered to provide force continuously. The vertical column allows motions of the pelvis and torso at the same time.

Figure 2-12: KineAssist prototype (a) and in operation (b) [20]

KineAssist includes a trunk and pelvis mechanism to allow bending motions for left-right, forward-backwards, and rotations about a person's transverse axis, as well as the hip rotation about the forward axis. Among all the DoFs of KineAssist highlighted in Figure 2-12, only two DoFs are actuated (forward bending of the trunk and lateral bending of the trunk). The collapse of the trunk is prevented by having a torso mechanism attached at the chest level. These mechanisms allow the patient to walk naturally while the safety of the patient is ensured. Falls are likely to happen during the patient's walking with KineAssist. Nevertheless, KineAssist is designed to slow and stop the fall of the patient without inducing pain. It can safely bring a patient to a stop after a few inches of fall. The threshold distance for identifying and stopping a fall can be selected by therapist.

Unlike the systems reviewed in previous session, KineAssist is designed as a tool for therapist, the system itself does not provide physical therapy. The major advantage of this system is the realization of body weight support module. Instead of using cable-harness body weight support concept, KineAssist provides body weight support through the robotic arm. Simultaneously, the robotic arm provides the necessary freedom for natural pelvic and trunk movement. Compared to cable-harness body weight support, KineAssist does not have the constraint of pelvic motion imposed by the body weight support setup.

Since KineAssist is developed as an assistive tool for therapist, the main purpose of the system is to maintain the balance of patient during walking. The robotic arm design is not capable of providing assistance to pelvis to complete pelvic motion training for walking. The lack of lower limb robotic orthosis make it not suitable for patient in a much severe condition, where by lower limb motion guidance is required to complete walking locomotion.

Figure 2-13: DoFs in (a) Trunk control mechanism; (b) Pelvis control mechanism [20]

2.3.4 Summary of Review on Robotic Gait Rehabilitation Devices

In general, robotic gait rehabilitation systems can be categorized into three groups. Some typical devices belong to each group developed for specific purposes are introduced in the previous section. Each group has some limitations highlighted as follows:

Group 1: BWS treadmill training system

- DoFs of pelvis such as rotation, obliquity, and horizontal are restricted.
- Patients may not feel a natural walking gait pattern on treadmill.
- Need more space, heavy so that it's not easy to move the system from one place to another.
- The price is more expensive because of treadmill.

Group 2: Footplate based training system

- DoFs of pelvis are constrained.
- Hip and knee joint angle trajectories are not controlled.

Group 3: Over ground walking training system

- Pelvis motion guidance is limited by the overhead BWS system (WalkTrainer)
- KineAssist aims to maintain the balance for the patient without guidance for pelvis and lower limb motion.

2.4 Review of Gait Pattern Planning for Robotic Assisted Gait Rehabilitation

2.4.1 Gait Description

Gait planning and customization is one of the key concerns for robotic assisted gait rehabilitation. Before using robotic assisted gait rehabilitation for patients suffered from Spinal Cord Injured (SCI) and stroke, gait pattern should be planed and tailored to the patient [12, 58].

Good understanding of gait analysis is necessary before planning and customizing for gait pattern. It is also essential in diagnosis of gait impairment. There are two basic human gait patterns: walking and running. This section will review on gait analysis of human walking.

One gait cycle is defined by the two consecutive heel strikes of the same leg. A gait cycle contains two phases: stance phase and swing phase. Stance phase is the time when the foot in contact with the floor. Stance phase begins with the heel strike and ends with the toe off for the same foot. It contributes about 60% in total time of a gait cycle. On the other hand, swing phase happens when the foot is not contact with the floor. Swing phase begins when one foot lift up and ends when this foot touches the floor again. Swing phase makes up the other 40% of the gait cycle.

It is important to know the terminology before analyzing the stance phase and the swing phase. Besides traditional terminology used to describe the components of walking, some other terminologies are also developed. Among them, the terminology created by the Gait Laboratory at Rancho Los Amigos Medical Center, RLA terms, is widely accepted. Traditional terms refer to the points or events in gait cycle whereas RLA terms refer to periods in gait cycle. The comparison of traditional terms and RLA terms is introduced in Table 2-1.

2.4.1.1 Stance Phase

As mentioned previously, stance phase is the period when the foot is in contact with the floor and it contributes about 60% of a gait cycle. Based on traditional

terminology, stance phase contains five events which are heel strike, foot flat, midstance, heel off and toe off. Stance phase is illustrated in Figure 2-14.

Figure 2-14: Components of stance phase [81]

Heel strike happens when the heel first contact with the floor after the swing phase. Ankle angle is in neutral position. After heel strike, foot flat occurs at about 7% in one gait cycle. During this event, the foot is flat on the floor. At about 30% of a gait cycle, the body weight is transferred to the weight bearing foot and this event is referred as midstance. At about 40% of a gait cycle, the heel rises and do not contact with the floor. This event is heel off. Stance phase ends at about 60% of a gait cycle with toe off. Toe off is the instance when the toe lifts off from the floor and start the swing phase.

In the view of RLA term, one gait cycle contains of five periods: initial contact, loading response, midstance, terminal stance and pre-swing. Initial contact is identical to heel strike in traditional term. Loading response is the period from heel strike to the other foot toe off (0% to 10%). Midstance in RLA term is the period from 10% to 20%. From 20% to 50% of one gait cycle is the period of terminal stance in RLA term. The last period in stance phase in RLA term is pre-swing which is from 50% to 60% of one gait cycle.

2.4.1.2 Swing Phase

According to traditional terminology, a swing phase is divided into three components: acceleration, midswing and deceleration. There are three components of swing phase if using RLA terminology: initial swing, midswing and terminal swing. The components of swing phase are illustrated in Figure 2-15.

Figure 2-15: Components of swing phase [81]

Acceleration is the first component of swing phase. This event happens right after the toe lifts off from the floor and starts to swing. At about 75% of gait cycle is the event of swing phase. At about 85% of gait cycle, the leg will start to decelerate and about to heel strike. This event is defined as deceleration.

In RLA term, initial swing is the period between the end of toe off and the end of acceleration (about 60% to 73% of gait cycle). Midswing phase is the period between midswing in traditional term and deceleration (73% to 87% of gait cycle). The final period of swing phase in RLA term is terminal swing which is from deceleration event to the event right before heel contact (87% to 100% of gait cycle).

Table 2.1: Comparison of gait terminology

Traditional		RLA	
Terminology	Definition	Terminology	Definition
Stance phase			
Heel strike	Heel contacts with floor	Initial contact	Heel contacts with floor
Foot Flat	Plantar surface of the foot in contact with the floor	Loading response	Start: After initial contact. End: Toe off of the other leg
Midstance	Event that the body weight is transferred to the weight bearing leg	Midstance	Start: Toe off of the other leg End: Body is directly over the weight bearing limb
Heel off	The heel starts rising from the floor	Terminal stance	Start: Heel of the weight bearing leg rises End: initial heel contact of the other leg
Toe off	Toe lifts off from the floor, end of the stance phase.	Preswing	Start: initial heel contact of the other leg End: Right before the toe off of weight bearing leg.
Swing phase			
Acceleration	The swing leg begins to move forward	Initial swing	Start: Toe off End: Knee joint of swing leg in maximum flexion
Midswing	The swing leg is directly under the body	Midswing	Start: Knee joint of swing leg is in maximum flexion End: The swing leg has moved in front of the body and the tibia is in a vertical position
Deceleration	The swing leg start to decrease velocity and prepare for heel strike	Terminal swing	Start: The tibia is in vertical position End: Just prior to initial contact.

2.4.1.3 Normal Gait Profile

A good understanding of normal gait profile is crucial for planning a proper gait pattern in rehabilitation training process. It is also useful for evaluating the therapeutic process. For a human to walk properly, gait involves the coordination of the three lower limb joints which are the hip, knee and ankle joints. These lower limb joints need to rotate to a particular degree at a particular timing to generate a normal walking gait pattern. The lower limb joint angles for normal walking in sagittal plane are illustrated in Figure 2-16.

Figure 2-16: Lower limb angles (hip, knee and ankle angles) in the sagittal plane for normal gait. Solid lines represent the mean value and dotted lines indicate the standard deviation values[81]

2.4.2 State of The Art of Gait Pattern Planning

To maximize therapeutic outcome, it is crucial to induce a gait pattern that resembles natural human gait pattern during gait rehabilitation [54, 58]. In the view of the three principles of gait rehabilitation, planning the gait pattern for the training process will help to achieve the second principle, specificity. In the context of practicing correct kinematic gait patterns in a repetitive manner, little attention has been diverted to the study of gait pattern used in various gait rehabilitation system. In manual assisted BWS treadmill gait rehabilitation, the therapist moves the patient leg and pelvic using visual feedback and “feel”. The assistance provided can vary greatly between therapists and between training sessions [23].

In comparison, robotic orthosis found in gait rehabilitation systems adopt simplified approach to replicate the leg kinematics [18, 24]. Lokomat took a step further by allowing the gait pattern to be set according to the patient’s height and range of motion of the lower limb joint [73]. The BWS apparatus restricts pelvic motion, causes the modification of pelvic motion planning. The restricted pelvic motion are planned according to the lower limb motions and desired foot trajectory [82]. Apparently, most of the motion planning is template based, whereby a motion template of subject with anatomy parameters similar to the targeted subject is required. Template based planning needs a wide range of template collection, which is not efficient. The state of the art of the gait pattern planning is illustrated in Figure 2-17.

Figure 2-17: State of the art of gait pattern planning

Every individual has a certain personal peculiarities superimposed on the basic pattern of bipedal locomotion during walking. Hence, gait planning plays an important role in robotic gait rehabilitation. The importance of tailored gait pattern is obvious, as the patients learn the gait pattern imposed to them during the gait rehabilitation session.

Although it is known that normal gait pattern is preferred, a proper method to plan normal gait pattern is missing. To the author's knowledge, there is no other work focused on the predicting/planning of natural gait parameters for human. The most relevant research work in this area is normalized gait parameters formula highlighted by Inman *et al.*[83]. The formula described a linear relationship between stride length, cadence, and body height. The normalized gait parameter is given by:

$$\frac{stride_length}{cadence \times body_height} = 0.008 \quad (2.1)$$

Equation (2.1) is derived by fitting a straight line to the experimental data. However, the relationship of these parameters may not be represented by a simple linear function.

2.4.3 Gaps in Research on Gait Pattern Planning

As mentioned in Section 2.4.2, there are two existing strategies to generate the desired gait pattern. The first strategy is using available data from literature. Human kinematics were studied and lower limb joint angles of healthy subjects walking normally were recorded and presented in some textbooks [29, 84]. Robotic devices such as WalkTrainer[85], Driven Gait Orthosis (DGO) [18] select the averaged lower limb joint angle traces from textbook and use them as reference trajectories in the training process. On the other hand, desired trajectories for assisted gait training robot such as ALEX [27] and Gait Trainer GT-I [86] can be obtained from their own database. Some templates of desired ankle trajectories were constructed from healthy subjects. A template is chosen for training process when healthy subject's dimensions, primarily thigh and shank length, closely match with the patient's.

However, these two strategies have some disadvantages. Firstly, there are variations of the overall patterns for the hip, knee and ankle [29]. Therefore, using an averaged trajectory of normal walking people for patients with different anatomy is not appropriate. In the second strategy, the number of healthy subjects involved to determine target trajectory is small. Moreover, gait pattern not only depends on thigh and shank length but also depends on some other parameters such as age, gender, weight and height. Therefore, more data and more detail of mapping algorithm are required to generate a suitable gait pattern for a specified patient.

2.5 Review of *Subject-cooperative* Control Strategies for Robotic Gait Rehabilitation

2.5.1 Rationale for *Subject-cooperative* Control Strategies

Originally, robotic rehabilitation devices only moved the patient along predefined trajectories and did not adapt their movements to the activity of the patient. This position controlled training also known as passive training is well suited for patients who are in the early phase of rehabilitation or severely affected. However, passive training strategy does not provide an ideal training for patients who have capability of some voluntary motor control. If patients are trained with totally passive training

strategy, they tend to train with reduced activity of muscles and metabolism. For example, people with SCI who walk in a robotic gait training device with position control consumed 60% less energy than in traditional therapist assisted therapy [30]. On the other hand, if patients try to walk actively while the robotic rehabilitation device remains passively support, they will work against the resistance of the device, which result in abnormal muscle activity patterns [31].

To address those limitations mentioned above, *subject-cooperative* control strategies are being developed by many research groups [26, 27, 32-37, 39-43]. *Subject-cooperative* control strategies will recognize the patient's movement intention and muscular effort, display the information to the patient and therapists by some biofeedback sensors and adapt the robotic assistance to the patient's contribution during training session. The ideal control strategy will do the same as an experienced therapist, it will assist the patient's movement only as much as needed and inform the patient how to use voluntary muscle efforts and motion strategy [44].

Cooperative control strategies are expected to stimulate active participation from the patients. These control strategies also have the potential to increase the motivation of the patient because the changes in muscle activation will be reflected in the walking pattern which they can see on the fly via some biofeedback sensors. Therefore, it is assumed that Assist As Needed control strategies will maximize the therapeutic outcome. The overview of Assist As Needed control is shown in Figure 2-18.

Figure 2-18: Overview of *subject-cooperative* control strategies

2.5.2 Three Principles of *Subject-cooperative* Control Strategy

The term cooperativity indicates interactivity, adaptivity and flexibility.

➤ **Interactivity:**

There is bidirectional exchange of information between robotic rehabilitation device and patient during the training process. The information from patient to robot such as ground reaction force (GRF), electromyography (EMG), kinematic information, etc are captured by using sensors. On the other hand, information such as ankle trajectory, gait event, lower limb angle, etc are displayed online via screen to patient to help them to be involved in the training process.

➤ **Adaptivity:**

Based on the information flow between robotic device and patient, the controller from the robot will calculate how and how much it will support the patient in the next step. On other words, the robot is able to adapt its reaction to the patient's movement and bio information.

➤ **Flexibility:**

The robot's mechanical design has to be flexible to react softly and gently to the patient's muscular effort.

2.5.3 State of the Art of *Subject-cooperative Control Strategy*

2.5.3.1 Automatic Gait Pattern Adaptation Algorithm

In 2004, Lokomat research group focused on the development of the algorithms for automatic gait pattern adaptation to allow the patient to walk actively in the training process [35]. This control algorithm based on the hypothesis that the interaction forces (torques) between Lokomat system and patient should be minimal in the case of synchronized movement between these two coupled systems and increase in the case of desynchronization. In this algorithm, lower limb angle trajectories were adjusted to minimize human-machine interaction torques as follows:

$$\begin{aligned} J(\delta q_r, F_1, F_2) &= \sum_k \left\| \tau_{PAT,ACT}(F_1, F_2)_k - \delta\tau(\delta q_r)_k \right\|_2^2 \\ \delta q_{r_adapt} &= \arg \min_{\delta q_r} J(\delta q_r, F_1, F_2) \end{aligned} \quad (2.2)$$

where F_1 and F_2 are the measured ball-screw forces; $\tau_{PAT,ACT}$ is additional active torque component produced when the patient influence the gait voluntarily; $\delta\tau(\delta q_r)$ is the variation in torque produced by variation in the reference joint trajectories δq_r ; and k is one instance in walking gait cycle.

The torque variation $\delta\tau(\delta q_r)$ is calculated from the mathematical model as the following equation:

$$\begin{aligned}\delta\tau(\delta q_r) = & M_{PAT+ORT}(q_r + \delta q_r)(\ddot{q}_r + \delta\ddot{q}_r) + C_{PAT+ORT}(q_r + \delta q_r, \dot{q}_r + \delta\dot{q}_r) \\ & + G_{PAT+ORT}(q_r + \delta q_r) - M_{PAT+ORT}(q_r)\ddot{q}_r \\ & - C_{PAT+ORT}(q_r, \dot{q}_r) - G_{PAT+ORT}(q_r)\end{aligned}\quad (2.3)$$

where $M \in \mathbb{R}^{2 \times 2}$ is a symmetric, positive definite inertia matrix; $C \in \mathbb{R}^2$ represents the Coriolis and centrifugal torques, and $G \in \mathbb{R}^2$ represents the gravity torques.

2.5.3.2 Adaptive Impedance Control Algorithm

This is another patient cooperative control strategy developed by the Lokomat research team [38]. For this algorithm, instead of having the gait pattern change after several steps, this approach works with a constant reference trajectories with impedance controller parameters adaptation. The desired reference trajectory was obtained from a single healthy subject and it scalable in both spatial and temporal space for individual gait requirements. In order to extract the "active" joint moment contributions from the subject, an inverse dynamic model of the subject and the Lokomat system was derived as follows:

$$\begin{aligned}\tau_{act} = & [M_L(q) + M_H(q)]\ddot{q} + C_L(q, \dot{q}) + C_H(q, \dot{q}) + G_L(q) + G_H(q) \\ & - \tau_{pas}(q) - \tau_{int}\end{aligned}\quad (2.4)$$

where $M(q)\ddot{q}$, $C(q, \dot{q})$ and $G(q)$ represent the inertial, coriolis, and gravitational moments of the human subject (index H) and the Lokomat system (index L), respectively; $\tau_{pas}(q)$ are passive elastic joint moments which are available for a group of healthy subjects as well as paraplegic subjects [87, 88]; τ_{int} represents the interaction moment exerted between the Lokomat and the patient. Note that the estimation of subject's active joint moment is only valid for the swing phase of gait as no ground reaction force was included in (2.4).

Figure 2-19: Admittance control architecture used to make the Lokomat behavior compliant a joint-space controller[38]

The estimated active joint moment τ_{act} is fed into a virtual admittance function to determine the joint angle deviation Δq from the reference joint angle trajectories q_d . The virtual admittance function in this algorithm, by definition, is the inversion of the following impedance function:

$$\tau_{act} = K\Delta q + B\Delta \dot{q} \quad (2.5)$$

where K and B are the virtual linear elastic and linear viscous coefficients, respectively.

The resulting new reference position $q_d^* = q_d + \Delta q$ is then fed into a proportional-derivative (PD) position controller.

The virtual impedance controller parameters are adjusted based on the effort from the subject which can be estimated from force sensors. The controlled impedance (stiffness, damping, and inertia) is set high when there is a little effort made by the patient. The impedance magnitude will be reduced as soon as an increased patient effort is detected. The lower the impedance magnitude, the greater deviations from the reference trajectory is possible. The behavior of the algorithm is that it guides the patient along the fixed reference trajectories when the patient can't make any effort, and allows for larger deviations when the patient tries to walk in his/her pattern. Adaptive controller is incorporated in the impedance controller, which allows the modification of the impedance parameters based on the patient's performance during the training course.

2.5.3.3 Virtual Force/ Velocity Field Control Strategy

In 2006, Cai *et al* developed two algorithms for Assist As Needed (AAN) strategy in gait rehabilitation which are “Band” and “Window” [17, 89]. The first strategy implements two fixed boundaries: an inner bound and an outer bound, forming a “band” surrounding the reference trajectory. This approach is shown in Figure 2-20. When the ankle position in sagittal plane stays within the band, it is guided by a small constant velocity field tangent to the desired trajectory. But the velocity field does not enforce specify timing of leg movement along the trajectory. When the ankle leaves the band, the convergent velocity fields will move it back to the band region.

Figure 2-20: Variability training paradigm I (Band). The desired training trajectory is in thick blue. The dotted red lines represent the boundaries within which “soft control” is applied. The arrows is the velocity fields that drive the leg to the band region [89]

A clockwise outward spiraling velocity field inside a unit circle is determined by the following equations in the polar coordinate r, α :

$$\begin{aligned}\vec{v}_r(r, \alpha) &= (1-r)(\vec{i} \cos(\alpha) + \vec{j} \sin(\alpha)) \\ \vec{v}_a(r, \alpha) &= k(-\vec{i} \sin(\alpha) + \vec{j} \cos(\alpha))\end{aligned}\tag{2.6}$$

A inward spiraling velocity field can be generated by reversing the direction of the angular component of the velocity field in (2.6).

The “window” strategy is basically analogous to the first strategy, but based on a moving “window” geometry. In the approach, a circular “window” moves along the

desired trajectory to provide the loose timing control (Figure 2-21). Within the window, the ankle is guided by a small constant velocity field which is tangent to the desired trajectory, but does not enforce specify timing inside window. Outside the window, a radio velocity field points inward to put the ankle back to the window. The magnitude of the velocity is proportional to the distance from the circle center:

$$v = k.(d - r) \quad (2.7)$$

Figure 2-21: Variability training paradigm II (Window) [89]

In 2007, ALEX (Active Leg Exoskeleton) research group introduced the force field control strategy for Assist As Needed (AAN) paradigm [27, 39]. The goal of the force field controller is to create a virtual force field around the reference trajectory of the foot in the sagittal plane in addition to providing damping to it. The structure of force field controller is illustrated in Figure 2-22. A typical shape of a virtual force wall is shown in Figure 2-23.

Figure 2-22: A force field controller [39]

Figure 2-23: A Cartesian plot of the foot in the trunk reference frame, origin set at the hip joint. The solid line is the desired trajectory of the foot and the dashed lines are the virtual wall [39]

The forces applied on the foot contain of tangential force F_t , normal force F_n to the desired trajectory and damping force F_d . The tangential force moves the foot along the trajectory when the foot is inside the tunnel, the normal force put the foot back to the virtual tunnel when it moving outside and the damping force limits the velocity.

The normal force which is used to generate the virtual walls is defined as follows:

$$F_n = \begin{cases} K_n \left(\frac{|d| - D_0}{D_n} \right)^2 \hat{n}, & \text{if } |d| > D_0 \\ 0, & \text{otherwise} \end{cases} \quad (2.8)$$

where d is the distance from the ankle point (point **P** in Figure 2-23) to the nearest point on the reference trajectory (point **N** in Figure 2-23); D_0 is defined as the tunnel width; D_n and K_n are constant numbers with length unit and force unit, respectively; and $\hat{n}$ is a unit vector pointing from **P** to **N**.

The tangential force is defined as follows:

$$F_t = \begin{cases} K_{F_t} \left(1 - \frac{d}{D_t} \right) \hat{t}, & \text{if } \frac{d}{D_t} < 1 \\ 0, & \text{otherwise} \end{cases} \quad (2.9)$$

where K_{F_t} and D_t are constants. K_{F_t} is used to change the magnitude of the tangential force.

2.5.3.4 Path Control

Path control algorithm is introduced by Lokomat research group in 2010 [26]. This strategy generates a virtual tunnel around the reference trajectory by an adjustable dead band of width w_{db} . Within the tunnel, the controller is in “free run”

mode, the output τ_{cor} of the impedance is zero and the gravity and friction torques of the robot are compensated. Thus, the patient will be able to move freely and with their own timing as long as they stay within the tunnel. The correction torque τ_{cor} is defined as follows:

$$\tau_{cor} = K\Delta\tilde{q} + B\frac{d}{dt}\Delta\tilde{q} \quad (2.10)$$

where K and B are spring constant and damping constant, respectively; spring constant K and distance $\Delta\tilde{q}$ to the tunnel wall is defined as follows:

$$\begin{aligned} \Delta q &= q_{ref}(S) - q_{act} \\ \Delta\tilde{q}^{(i)} &= \begin{cases} \Delta q^{(i)} - \frac{1}{2}w_{db}^{(i)}, & \Delta q^{(i)} > \frac{1}{2}w_{db}^{(i)} \\ \Delta q^{(i)} + \frac{1}{2}w_{db}^{(i)}, & \Delta q^{(i)} < -\frac{1}{2}w_{db}^{(i)} \\ 0, & |\Delta q^{(i)}| \leq \frac{1}{2}w_{db}^{(i)} \end{cases} \\ \tilde{K}^{(i)} &= c_K^{(i)} \|\Delta\tilde{q}\|^2 \\ K^{(i)} &= \min(\tilde{K}^{(i)}, K_{\max}^{(i)}) \\ K &= \begin{pmatrix} K^{(1)} & 0 \\ 0 & K^{(2)} \end{pmatrix} \end{aligned} \quad (2.11)$$

where $c_K^{(i)}$ are constants which were determined by trial and error.

Besides the correction torque, adjustable supportive torques are also added to the controller output for helping the patient to overcome their weaknesses. The directions of the supportive torque vectors are tangential to the movement path in joint space. The impedance controller will provide τ_{cor} to correct the leg posture of the patient when it moves outside the tunnel. An optional “moving window” moving at the velocity specified by the therapist along the trajectories can be added to correct the velocity of the leg during swing phase. When the patient moves faster or slower than the pre-defined velocity, the patient will reach the “front wall” or “back wall” of the window and he/she will be put back to the window. The block diagram of path control strategy is shown in Figure 2-24.

Figure 2-24: A block diagram of path control strategy[26]

2.6 Gaps in Current Research

2.6.1 Gait Pattern Planning

As mentioned previously, generating a healthy human's gait pattern is critical for the gait rehabilitation process. There are two major strategies to generate the desired gait pattern. The first strategy is using available data from literature and the second one is choosing from database of healthy subjects' gait patterns. The two strategies have some limitations on accuracy and efficiency. Therefore, the problem of gait pattern planning for gait rehabilitation training has not been satisfactorily addressed.

2.6.2 Pelvic Control

Human gait locomotion consists of six determinants, which are pelvic rotation, pelvic tilt, stance phase knee flexion, knee mechanisms, foot mechanisms, and lateral displacement of the pelvis [90]. Three out of six of these determinants are pelvic related movements, which highlight the important of pelvic control during gait rehabilitation. As mentioned, the pelvic motion significantly affects human's gait. The lack of pelvic control on patient will result in alteration of gait pattern, which should be avoided [91]. However, there is no Assist As Needed control strategy applied in pelvic motion until now. Most of the devices only focus on controlling the lower limb of the patient in Cartesian or in joint space.

2.6.3 Control Space

The literature review shows that most of the rehabilitation devices implement the control strategies in Cartesian space for foot or ankle joint trajectories. However, it is possible that training the subjects in Cartesian space might change their gait pattern [26]. Some research groups, i.e. Lokomat, decide to control the robot in joint space rather than Cartesian. However, they still have some limitations on the number of degree of freedom (DoFs). In order to implement the Assist As Needed control strategies by using the virtual “tunnel” in joint space, the controllers allow some specified variation around the fixed reference lower limb angle trajectories. This approach can help the patient move “freely” within the tunnel but might not warranty for the heel contact in the gait cycle.

2.6.4 Control Algorithms

- Automatic Gait Pattern Adaptation Algorithm

Automatic gait pattern adaptation algorithm for active control which updates the reference trajectories after several gait cycle can allow the patient to contribute their effort during the training process. This approach is good for those who are strong enough to make their effort. However, if the patients are weak and can't make their effort, this strategy will become totally position control. This strategy required several gait cycle for estimating the human-robot interaction torque and updating the trajectories. Therefore, the response of this active controller might be a concern.

- Virtual Force/ Velocity Field Control Algorithm

Virtual Force/Velocity Field control will create a virtual “tunnel” around the reference trajectory of foot position or ankle position. The patient can move his/her foot freely as long as the foot or ankle stays in the “tunnel”. In other words, the reference trajectory is flexible in both spatial and temporal. However, after the virtual “tunnel” is defined, the width of the tunnel is fixed during the training process. The controller can perform better if there are some parameters taken into account to modify the wall based on the performance of the patient. The virtual force/velocity field is now implemented in Cartesian space which is can affect the patient's natural gait pattern after the training course.

- Path Control

Path control is the most recent control strategy which is introduced in 2010. It's quite similar to force field control but the trajectories in joint space are controlled rather than in Cartesian space. The width of the "tunnel" also can't be modified during the training process. The lower limb angles have some deviation in which the patient can move freely inside. It may not warranty the heel strike of the patient. Therefore, the widths of these "tunnels" have to be tight enough for natural gait pattern and the patient most likely is trained outside the "tunnel". There is an impedance control outside to drive the patient back to the "tunnel". The parameters of this impedance controller are also unchangeable, thus, the deviation provided by the virtual mechanical impedance is remained while the patient's performance changing.

2.7 Concluding Remarks and Overview of Research Approach

2.7.1 Concluding Remarks

In this chapter, reviews of clinical and engineering aspect in gait rehabilitation are presented. Clearly, body weight supported gait rehabilitation enable the disabled patient to train for walking. This is previously not possible with the traditional training approach. Commonly, the body weight supported gait rehabilitation is carried out on treadmill. Over the last 10 years, studies have shown that SCI and stroke subjects who receive body weight supported treadmill training demonstrate improved EMG activation patterns, more natural walking characteristics, increment in weight bearing on their legs, and demonstrate functional improvement in walking ability. Review of these evidences can be found in [15].

Robotic system for body weight supported gait rehabilitation is introduced to address the limitation of the therapist assisted body weight supported gait rehabilitation. Most of the robotic systems provide lower limb assistance in the similar manner with little attention focused on the pelvic motion guidance. It could be partially due to the body weight support apparatus used in majority of the robotic systems, which inhibit the assistance of unrestricted pelvic motion. Cable-harness body weight support apparatus secures pelvis rigidly in place, disallow natural pelvic movement during gait rehabilitation. With this restriction, body weight shifting is made impossible.

To conclude this chapter, it is found out that there is a need to address the issue on natural gait-like walking pattern and active participation of patient in rehabilitation. Individual-specific gait pattern planning will fulfill the one of the three principles of rehabilitation which is specificity. Active participation ensures the patient uses own effort as much as possible during the gait training. According to the principle of gait rehabilitation, a high degree of participation and involvement of individuals are required to facilitate motor learning [49, 50]. However, it is noteworthy that robot will never be able to replace the interpersonal contact of therapist and patient, which is so necessary for rehabilitation. It is only an additional option to intensify therapy [65].

2.7.2 Research Approaches

The literature review in both clinical and engineering aspects provides valuable background information, forms the basis of the research methodology proposed in this research work. With the research requirements laid down in the research methodology, engineering realization convert the idea into robotic gait rehabilitation. The engineering realization do considers the opinion given by doctors and therapists, as a form of clinical requirements for the engineering realization. This research work categorized targeted patients according to their physical condition after lesion, and the robotic rehabilitation system are designed for the selected groups of patient.

Figure 2-25: Overview of research approach

The developed robotic rehabilitation system undergoes two trial cycles. Prototype trial is arranged to test the system on healthy subject. The feedback collected during prototype trial will be used to improve the system. After the improvement, clinical trial will be arranged for testing the robotic system with patients in a local hospital. The feedback collected during clinical trial will be analyzed for future improvement of the robotic system. The overview of the research approach is provided in Figure 2-25.

The main focus for this research work is the creation of new methodology for robotic assisted gait rehabilitation, the realization of the proposed features in the methodology via engineering approach, and eventually the trials of the robotic gait rehabilitation. The methodology for gait rehabilitation and engineering realization are further categorized into four areas:

1 Gait Study

- The main aim of this gait study is to fill the gap of current research in the gait pattern planning. A methodology for gait pattern specifically generated for targeted subject is introduced. Gait parameters and waveform of the lower limb joint angles will be generated based on the some input parameters. Details will be discussed in Chapter 3.

- The motion capture data will be used as the predefined motion input (reference trajectories) for the passive control strategy of the proposed robotic system.

- The range of motion for every joint involved in the locomotion training will be carefully studied. Hardware limits and virtual constraints will be implemented to ensure the gait rehabilitation system will not travel beyond the patient's acceptable range of motion during the gait rehabilitation session.

2 Robotic System

- The design and development of robotic system for the realization of gait locomotion assistance, pelvic motion assistance, and body weight support, in the over-ground context for targeted patient.

3 Control Strategy

- An overall control system will be developed, consists of programmed controller for controlling each motion of the system, and provide a Graphical User Interface (GUI) to allow the user (doctor/therapist) to make necessary change to the gait rehabilitation process (for example, walking velocity for the training). The control system can be programmed to enable different rehabilitation control strategies based on specific rehabilitation requirement.

- This project will study the feasibility of implementing active assistance for gait rehabilitation using biological-signals (for example, EMG) and gait parameters.

4 Bio-feedback

- Bio-feedback provides the essential bio-signal feedbacks, e.g. ground reaction force, electromyography signal, gait events, and etc. The bio-feedback serves two main objectives: visual feedback for assessment, and feedback for implementation of control algorithm.

Chapter 3

INDIVIDUAL-SPECIFIC GAIT PATTERN PLANNING FOR ROBOTIC ASSISTED GAIT REHABILITATION

Task specificity has been proved as one of the major principles for rehabilitation. The best way to improve performance of a motor task is to execute that specific motor task again and again [22]. Edgerton *et al* have concluded that training exerts its effects mainly through central mechanisms and not peripheral muscular mechanisms [92-95]. It has been illustrated that animals with complete transections of the spinal cord that were trained to walk or stand attained a different level of performance. The animals were trained specifically to walk will walk better than animals that were trained only to stand whereas animals were trained to stand performed better standing than animals trained to walk. That could probably explain why patients with neurological disorder who have been trained with conventional rehabilitation approach, such as passive bracing, would not improve in locomotor function.

Task specific training approach could be more powerful than conventional treatment with traditional concepts [56, 96]. Conventional approaches or nonspecific rehabilitation approaches such as passive stretching [3], acupuncture, or general home exercise [4] have no beneficial effects on functional locomotor outcomes. Similar observations have been found with balance training. Dickstein *et al*[97] reported an improvement in balance during standing when stroke patients had been trained to shift weight onto the hemiparetic side. However, functional locomotor outcomes haven't found to be improved. The findings have illustrated the importance of task specific training approach.

Robotic gait rehabilitation systems require a pre-defined pattern of gait locomotion, in order to carry out the gait training. To achieve an optimal afferent input to the spinal cord and maximize the functional locomotor outcomes, the pre-defined movement inputs should be in physiological manner or natural gait-like pattern [18, 22]. In manual assisted BWS treadmill gait rehabilitation, the therapist moves the patient leg and pelvic using visual feedback and “feel”. The assistance

provided can vary greatly between therapists and between training sessions [23]. In comparison, robotic orthosis found on those robotic gait rehabilitation systems adopt simplified approach to replicate the leg kinematics [18, 24]. Lokomat took a step further by allowing the gait pattern to be set according to the patient's height and range of motion of the lower limb joint [73].

Lower limb joint angles were well documented in the existing literature (e.g. CGA database [14]) and can be easily used for trajectory generation for robotic gait rehabilitation systems. Previous studies mainly used CGA data as the reference in their gait pattern planning [18, 25-28]. However, gait data in the CGA database were available only for certain individuals. Thus, the CGA data cannot well account for inter-individual differences. Furthermore, CGA data is limited to one recorded walking speed for each individual, and thus cannot allow the changing of walking speed in gait pattern planning.

In view of this limitation, *GaitGen*, a model for planning of gait pattern, was proposed [98]. The proposed model will generate a gait pattern for a given subject given his/her anthropometric data. The model consists of three stages as illustrated in Figure 3-1. The first stage introduces a prediction model for basic gait parameters: walking speed, stride length, and cadence. Second stage explores the generation of gait pattern based on basic gait parameters and anthropometric data. Third stage works on translating and coordinating the gait pattern for gait locomotion playback on robotic gait rehabilitation system.

Figure 3-1: Overview of the proposed model, *GaitGen*, for gait pattern planning of robotic assisted gait rehabilitation

3.1 *GaitGen* Stage I: Prediction of Individual-Specific Basic Gait Parameters for Over-ground Walking

Every individual displays certain personal peculiarities superimposed on the basic pattern of bipedal locomotion during walking. It has been known that gait pattern is significantly affected by gait parameters (stride length, cadence) [99-102]. Thus, an approach to predict the basic gait parameters of walking for individuals shall be

established to facilitate the planning of gait pattern. Inman *et al* introduced a normalized gait formula which attempted to ensure that the specified gait parameters are suitable for the patient, based on the patient's anthropometric data [83]. Normalized gait formula facilitates the generation of corresponding gait parameters based on the data from patient's anatomy, for example, body height. The normalized gait parameter is given by:

$$\frac{sl}{cad.h} = 0.008$$

where *sl* is stride length (cm), *cad* is cadence (steps/min) and *h* is body height of a subject (cm).

The normalized gait parameter equation was derived by fitting a straight line to the experimental data. However, the relationship of these parameters may not be represented by a simple linear function and the constant value 0.008 is not the same for all population [103]. Lim *et el* conducted experiments with a small group of students in Singapore and showed that the normalized gait parameters are varied from 0.006 to 0.0098 for different subjects [103].

This work aims to design a basic gait parameter prediction model that is able to generate self-selected slow or normal walking speed and the corresponding gait parameters of any individual given his/her age, gender, body height and weight. This work can provide reference of individual-specific basic gait parameters for therapists and doctors to facilitate gait pattern planning during gait rehabilitation. GAITrite experiment was carried out for 50 subjects with neither neurological injury nor gait disorder. Subjects' anthropometric data and their walking gait parameters were recorded to a database. The model consisted of two modules which are *WS-Module* and *SL-Module* for the prediction of walking speed and stride length, respectively. The two modules were constructed from Generalized Regression Neural Networks (GRNNs). At the first step, walking speed mode was selected (slow or normal walk) and *WS-Module* was applied to provide a range of walking speed to doctor/therapist as reference. After walking speed was selected, *SL-Module* would be applied to predict the corresponding stride length. Finally, cadence was calculated from walking speed and stride length. The accuracy of this work is compared to normalized gait parameters formula [83].

3.1.1 Methods

This work allows the therapists or doctors quickly obtain a reference set of suitable gait parameters for the targeted subject by specifying the desired speed state (normal or slow), and providing the basic information: age, gender, height, and weight, of the targeted subject.

The overview of gait parameters prediction model is shown in Figure 3-2. First, the state of walking speed (slow or normal walk) had to be chosen by therapist. When the walking speed mode was available and the basic information from the targeted subject was given, *WS-modules* would activate corresponding trained GRNN to predict a suitable walking speed. Since human do not walk at a fixed walking speed at self-selected walking pace, the *WS-module* was trained to provide a range of walking speed as reference. Therapist could select a suitable walking speed for targeted subject based on the recommended values. Experimental data from GAITRite revealed that walking speed fluctuates within a range when subjects were asked to walk at the self-selected speed. Walking speed of the 50 subjects ranged from 0.25% to 18.84% of the average walking speed of each individual. The cause of the variation was not studied in this work, but we would suggest the variation of walking speed was 5% for slow walking and 3.8% for normal walking of each individual's average walking speed. These values were based on the variability of walking speed from 50 subjects.

From the selectable range of walking speed provided by *WS-module*, a desired walking speed can be selected by doctor/therapist. Subsequently, the selected walking speed will become the input of the *SL-module* which will predict the value of stride length. Stride length prediction function will map a suitable stride length based on the selected walking speed and the anthropometric parameters of the targeted subject. Finally, cadence was calculated based on the selected walking speed and mapped stride length. The cadence is calculated as follows:

$$cad = 120 \frac{ws}{sl}$$

where *cad* is cadence (steps/min), *ws* is walking speed (cm/s), and *sl* is stride length (cm).

Figure 3-2: A gait parameters prediction model in robotic assisted gait rehabilitation[104]

3.1.1.1 Experimental Setup

Fifty healthy subjects (26 males and 24 females) with ages ranging from 17 to 51 years (mean 28 ± 10 years), height 150 - 189 cm (mean 166.2 ± 9.2 cm), and weight 37 - 85 kg (mean 59.6 ± 11.5 kg) were recruited from the population of Nanyang Technological University (NTU), Singapore. The general information of the recruited subjects is presented in Table 3.1. These subjects have neither neurological injury nor gait disorder. Each subject was instructed to walk three times at their self-selected slow walking speed and three times at their self-selected normal walking speed on

GAITRite system. GAITRite was used to record walking speed, and stride length of these subjects during their walks. An additional space of 2.5 meters was provided at the two ends of the GAITRite for the subject to enter the recording area at rhythmic walking stage. Experimental setup for gait parameters data collection is shown in Figure 3-3. Gait data collected included walking speed, cadence, and stride length. Experimental data is provided in Appendix-A.

Figure 3-3: A gait parameters experiment using GAITRite system

Table3.1: Information of subjects and number of walks

Numbers of subjects	Age	Height (cm)	Weight (kg)	Numbers of normal walks	Numbers of slow walks
50	17-51	150-189	37-85	150	150

3.1.1.2 Design of Neural Networks

Neural network is a prevalent analysis tool used in gait data studies in the last 10 years [105]. Neural network allows gait data to be analyzed with a highly flexible, non-linear modeling approach. The study of complicated gait variable relationships which have been difficult to be modeled analytically can be facilitated by the non-

linear property of neural network. In this work, generalized regression neural networks (GRNNs) were applied to predict walking speed and stride length because it has a high training speed and a strong non-linear mapping capability [106].

Based on existing literatures [99-102, 107] and preliminary analysis, we summarized that information from subjects such as age, gender, body height, and weight are the key factors that influence the basic gait parameters. This information was used as inputs to train GRNNs in *WS-module*. The inputs of GRNNs in *SL-module* are walking speed and body height which are the same as the inputs of normalized gait parameters formula.

To verify the concept proposed in this work using the relatively small sample size, the GRNNs in *WS-module* were trained 50 times using different subject each time as validation data. This method was known as cross-validation. The trainings were carried out by using 49 subjects as training data and a subject as validation data. With 50 trainings, the prediction accuracy of GRNN could be validated with all 50 subjects. The GRNNs in *SL-module* were trained 150 times with all walks data, different walk data was used as validation data for different training.

3.1.1.3 Selection of Smoothing Factors

GRNN consists of an input layer, a radial basis layer and a linear output layer. Each neuron in the hidden layer has a radial basis function to perform the nonlinear transformation from the input space to the hidden space. The Gaussian function is the common choice for the radial basis neurons and it is given by:

$$g(d) = \exp\left(-\frac{d^2}{2 \cdot \sigma^2}\right) \quad (3-1)$$

where d is the distance between two vectors and σ is the spread of Gaussian function or also referred as smoothing factor.

The smoothing factor plays an important role in function approximation [106, 108]. The function is steep if smoothing factor is small; therefore, neuron with weight vector closest to the input vector will give a much larger output than other neurons. As smoothing factor becomes larger, several neurons can respond to an input vector so that the function becomes smoother but the network becomes less selective. Therefore, optimal values of smoothing factors are required for GRNNs. In this study, the smoothing factor was evaluated and selected based on the least value of the

average Mean Square Error (MSE) of the predicted outcome. The average MSE are computed for GRNNs designed with smoothing factor values of 0.01 to 1. Each GRNN consists of 50 trainings as discussed in previous session.

The final smoothing factors selected for each function are summarized in Table 3.2. The example on the effect of smoothing factor measured in term of MSE is given in Figure 3-4

Table 3.2: Smoothing factor selected for corresponding GRNNs

	Walking Speed	Stride Length
Normal	0.250	0.150
Slow	1.000	0.175

Figure 3-4: Effects of smoothing factor measure on the predicted outcome for normal walking speed

3.1.2 Results

This section summarizes the results for the basic gait parameters predicted by the GRNNs using the selected smoothing factor. Mean absolute error of predicted outcome for walking speed $\bar{e}_{ws}$ and stride length $\bar{e}_{sl}$ of the 50 subjects was calculated and given in Table 3.3. The mean absolute error of stride length computed by using the normalized gait parameters formula was also calculated and shown in Table 3.3 for comparison. Predicted outcomes of the trained GRNNs with highest, lowest, and average mean absolute error are presented in Table 3.4. The complete result of the

predicted outcome is too lengthy and it is included as Appendix-B. The accuracy of trained GRNNs is summarized at Table 3.5.

Table 3.3: Mean absolute error of predicted outcome

	$\bar{e}_{sl}$ (cm)					
	$\bar{e}_{ws}$ (cm/s)		From <i>SL-module</i>		From [83]	
					$sl = \sqrt{0.96.ws.h}$	
	Slow	Normal	Slow	Normal	Slow	Normal
Average	270.45	223.82	31.63	19.96	84.58	56.34
Standard Deviation	393.63	334.81	60.12	27.35	112.50	100.00
Maximum	1937.84	1725.52	407.78	145.54	794.23	768.86
Minimum	0.09	0.10	0.00	0.00	0.03	0.02

Table 3.4: Predicted outcomes with the highest MSE, lowest MSE, and average MSE for the trained GRNNs

	Age	Gender	Height (cm)	Weight (kg)	Speed (cm/s)	Stride Length (cm)	Cadence (step/min)	Predicted Outcome	MSE
<i>Prediction Outcome of Normal Walking Speed</i>									
A	48	Female	158	43	85.17	109.18	93.60	126.71	1725.52
B	44	Male	168	67	111.09	121.15	110.03	126.00	222.26
C	25	Male	172	63	116.37	132.48	105.47	116.70	0.10
<i>Prediction Outcome of Slow Walking Speed</i>									
D	31	Female	165	65	45.68	105.54	51.77	89.70	1937.84
E	24	Male	185	75	100.63	138.66	87.10	82.73	320.67
F	26	Female	168	53	88.08	122.28	86.43	87.79	0.09
<i>Prediction Outcome of Stride Length (Normal Walking Speed)</i>									
G	25	Male	175	70	121.69	127.54	114.50	139.60	145.54
H	22	Male	162	60	106.49	127.79	100.00	132.31	20.42
I	22	Female	155	59	106.21	119.34	106.80	119.41	0.00
<i>Prediction Outcome of Stride Length (Slow Walking Speed)</i>									
J	48	Male	168	75	91.42	101.11	108.50	121.30	407.78
K	20	Female	172	58	60.50	93.32	77.80	98.72	29.15
L	22	Female	155	59	78.47	105.10	89.60	105.09	0.00

Table 3.5: Accuracy of trained GRNNs in predicting the basic gait parameters

		Accuracy		
Predicted outcome		> 95%	> 90%	> 80%
GRNN	Normal Walking Speed	32%	56%	90%
	Slow Walking Speed	24%	46%	81%
	Stride Length (Normal)	85%	100%	100%
	Stride Length (Slow)	74%	93%	100%
	Stride Length (Normal)	63%	95%	100%
Index	Stride Length (Slow)	39%	79%	98%

3.1.3 Concluding Remarks

The accuracy of the GRNNs for predicting slow walking speed is lower than the accuracy for predicting normal walking speed. A factor that could affect the accuracy of predicted outcome for slow walking speed is the difficulty in speed control during slow walk. It is obvious that the variation of walking speed during slow walk compared to normal walk is larger. Furthermore, we also needed to remind a few subjects to walk at their self-paced slow speed as they tend to walk at normal walking speed, especially toward the end of the experiment. Therefore some of the experimental data might not reflect the actual slow walking speed of some subjects.

The stride length was predicted using walking speed and height as the inputs for the trained GRNNs. The performance of the trained GRNNs was compared to normalized gait parameters formula and results are shown in Table 3.5. The results reveal that trained GRNNs are more accurate in predicting stride length as compared to the normalized gait parameters formula.

In general, it is expected that GRNNs has poor accuracy in predicting an outcome for targets that do not follow the general trend/pattern of the database. By referring to the predicted outcomes summarized in Table 3.4, those subjects with highest mean absolute errors of predicted outcome do not follow the general pattern of the population. For example, Subject ‘A’ and ‘D’ are walking at an extremely slow speed, compared to other subjects walking at the same state of walking speed. However, the

result in Table 3.4 should not be mistaken that GRNNs are predicting less accurate outcomes for older individuals. It is so happened that the subjects with highest MSE presented in Table 3.4 are older individuals.

To summarize, 56% and 46% of the GRNNs predicted outcomes are minimally 90% accurate in predicting slow and normal walking speeds. The accuracy of GRNNs trained for stride length is higher, 100% and 93% of predicted outcomes are at least 90% accurate.

3.2 *GaitGen* Stage II: An Individual-specific Gait Pattern Prediction Model Based on Generalized Regression Neural Networks

Locomotor training requires appropriate inputs to maximize functional recovery [21]. Specificity is one of the major principles of gait rehabilitation [22], which suggests that it is crucial to induce a gait pattern that resembles natural gait pattern of the specific targeted subject during gait rehabilitation. In this work, the human walking gait pattern is defined by three rotational movements of pelvis and lower limb joint angles in sagittal plane in one gait cycle.

Pelvic movements play an important role during human walking. Pelvic rotation and pelvic obliquity are considered as the first two of the six major determinants of human locomotion which presumably act to flatten the path of the body center of mass, thus reduce the vertical displacement of the body and decrease energy expenditure during human walking [109, 110]. In addition, pelvic rotation may be effectively used to increase stride length, especially at faster walking speed [110, 111]. Most of the current robotic assisted gait training devices have focused primarily on providing lower limb movements via lower limb orthosis. Several research groups have developed robotic assisted devices that incorporate pelvic orthosis (i.e., PAM/POGO, WalkTrainer) to allow pelvic motion which plays an important role in normal locomotion during the training process. PAM can be considered as a teach-and-play device that can drive the pelvis toward reference trajectories that either specified manually by therapists or pre-recorded from unimpaired subjects [75, 112]. To generate predefined pelvic trajectories that closely mimic natural movement of the targeted subject during gait rehabilitation training process, WalkTrainer research group introduced a pelvic amplitude prediction model. For implementation purpose, a simple linear model was used with only one input factor: walking speed. The model

assumed that pelvic motions always have the same shape and only their magnitude varies [113].

Lower limb joint angles were well documented in the existing literature (e.g. CGA database [14]) and can be easily used for trajectory generation for robotic gait rehabilitation systems. Previous studies mainly used CGA data as the reference in their gait pattern planning [18, 25-28]. However, gait data in the CGA database were available only for certain individuals. Thus, the CGA data cannot well account for inter-individual differences. Furthermore, CGA data is limited to one recorded walking speed for each individual, and thus cannot allow the changing of walking speed in gait pattern planning.

The objective of this work was to develop an individual-specific gait pattern prediction model that is able to generate walking gait patterns based on gait parameters (stride length, cadence) and anthropometric data of any target subject. Motion capture experiments of human walking were carried out and gait data were represented by Fourier coefficient vectors. A database which consisted of gait parameters, anthropometric data and Fourier coefficient vectors was constructed. From the database, a non-linear mapping function was designed and implemented to predict the Fourier coefficient vectors from given gait parameters and anthropometric data of the target subjects. Finally, the model applies inverse Fourier transform to generate the gait patterns using the predicted Fourier coefficient vectors. We hypothesized that the proposed model would be able to generate a gait pattern better than does the CGA approach in terms of resembling the actual gait pattern of the target subject.

3.2.1 Experimental Setup

Seventy healthy male subjects with ages ranging from 18 to 33 years (mean 23.6 ± 2.2 years), height 156 - 192 cm (mean 171.1 ± 6.2 cm) and body mass 49 - 120 kg (mean 64.3 ± 11.5 kg), were recruited from the general student population at the Nanyang Technological University (NTU), Singapore. These subjects have neither neurological injury nor gait disorder. Each subject was instructed to walk ten times at their self-paced slow and normal walking speeds on a twelve-meter linear walkway. The gait data was collected using an eight-camera motion analysis system (Eagle, Motion Capture Analysis Corporation) and the placement of fifteen reflective markers is illustrated in Figure 3-5 which is the same as in [114]. Anthropometric data of each

subject including ASIS breath, thigh length, calf length and foot length was also measured.

Figure 3-5: Marker placement on test subject during motion capture experiment
(Labels are inserted for visible markers only)[115]

3.2.2 Coordinate Systems and Pelvic Motion during Human Walking

The global reference frame was defined with respect to the motion capture laboratory. The x -axis corresponded to the line of progression and was positive in that direction. The y -axis was defined as perpendicular to the x -axis, parallel to the ground and was positive toward the left side. The z -axis was defined to make (x, y, z) a right handed triad.

There are three planes assigned to human body. Each of the planes is at right angle, or perpendicular to the other two planes. Sagittal plane divides the body into left and right sides. Frontal plane divides the body into front and back parts. Transverse plane also known as horizontal plane, which divides the body into top and bottom parts. Apart from the plane assignment, general coordination assignment

adopted in this work is, x and z axes form the sagittal plane, y and z axes form the frontal plane (as shown in Figure 3-6 a).

In general, pelvis can be modeled as a body with six DoFs, which consists of translational and rotational movements in three axes. Three translational movements consist of medio-lateral movement, anterior-posterior movement, and superior-inferior movement. The rotational movements are pelvic tilt, pelvic list and pelvic rotation. During gait locomotion, pelvic tilt occurs in sagittal plane, positive pelvic tilt involves the counter-clockwise rotation of the pelvis as viewed from the left side. Pelvic list occurs in frontal plane, positive pelvic list involves counter-clockwise rotation of the pelvis as viewed from the front. Finally, pelvic rotation occurs in transverse plane, positive pelvic rotation involves counter-clockwise rotation of the pelvis as viewed from above [110]. The mentioned movements are labeled in Figure 3-6 b.

Positions of the lower limb joint centers were estimated using the positions of the reflective markers and recorded anthropometric data. Subsequently a segment reference frame in pelvic segment was defined by the positions of hip joint centers and reflective markers [114]. The movements of the pelvis were considered with respect to the global reference system. Similarly, a segment reference frame in each lower limb segment was defined by the positions of lower limb joint centers and reflective markers. Joint angles were defined as a rotation of the distal segment frame relative to the proximal segment frame [114]. In this work, the lower limb joint rotations in the sagittal plane. Details of lower limb joint centers estimation, definition of reference frame and calculation of pelvic angles and lower limb joint angles are provided in Appendix-C.

Figure 3-6: (a) Movement definition of the pelvis, (b) Coordination assignment for left side (balloon L) and right side (balloon R) of the pelvis

3.2.3 Methodology of Gait Pattern Prediction

The model of gait pattern prediction for specific subject is illustrated in

. Fourier transform is a traditional spectral analysis method to describe any periodic signal in its harmonic components [105]. Since walking is periodic and the power for walking is supplied rhythmically with temporal consistency [29], Fourier transform was often used to describe the frequency content of gait [29, 116]. In this study, each pelvic angle waveform and lower limb joint angle waveform in one gait cycle was analyzed in the frequency domain and decomposed into one Fourier coefficient vector which consisted of eleven elements. A database which consisted of gait parameters, anthropometric data and Fourier coefficient vectors was constructed from the experimental data. Subsequently, a gait pattern prediction model for any specific subject was created based on this database. Non-linear mapping functions between the input vectors (gait parameters and anthropometric data) and Fourier coefficient output vectors were determined using generalized regression neural networks (GRNN). With these mapping functions, Fourier coefficient vectors were predictable given the gait parameters selected by clinical practitioners and anthropometric data measured from a specific subject. Inverse Fourier transform was then applied to generate pelvic angle waveform and lower limb joint angle waveforms for the subject.

Figure 3-7: The gait pattern prediction model for specific subject in robotic assisted gait rehabilitation

3.2.4 Extraction of Fourier Coefficient Vectors

Prior to the extraction of Fourier coefficients of the pelvic angle waveforms and lower limb joint angle waveforms, the cut-off frequency of the data must be determined. Power spectral density analysis was conducted on the collected experimental gait data and the average values were calculated. The results in Figure 3-8 and Figure 3-9 revealed that over 95.6% of the power of the pelvic angle waveforms and 96.2% of the power of the lower limb joint angle waveforms are contained below 6 Hz, respectively. Thus, the cutoff frequency of these signals was chosen to be 6 Hz. The result is agreed with previous studies, which suggested that the cutoff frequency for waking data should be set at about 6 Hz [29, 116].

Figure 3-8: Integrated power of pelvic angle waveforms

Figure 3-9: Integrated power of lower limb joint angles waveforms

Each pelvic angle waveform and lower limb joint angle waveform in one gait cycle can be decomposed to sinusoidal components as follows:

$$f(t_n) = \frac{1}{2}a_0 + \sum_{p=1}^{N/2} \left[a_p \cos\left(\frac{2\pi pn}{N}\right) + b_p \sin\left(\frac{2\pi pn}{N}\right) \right] \quad (3.2)$$

$n = 0, 1, \dots, N$

where a_p and b_p are the Fourier coefficients, and N is the samples taken for one cycle.

Fourier coefficients can be computed with the following formulas:

$$a_p = \frac{2}{N} \sum_{n=1}^N f(t_n) \cos\left(\frac{2\pi pn}{N}\right), p = 0, 1, \dots, \frac{N}{2} - 1 \quad (3.3)$$

$$a_{N/2} = \frac{1}{N} \sum_{n=1}^N f(t_n) \cos(\pi n)$$

$$b_p = \frac{2}{N} \sum_{n=1}^N f(t_n) \sin\left(\frac{2\pi pn}{N}\right), p = 0, 1, \dots, \frac{N}{2} \quad (3.4)$$

Since the sinusoidal components above 6 Hz are insignificant, the pelvic angles and lower limb joint angles for any sample point, n , in one gait cycle can be represented by:

$$f(t_n) = \frac{1}{2}a_0 + \sum_{p=1}^5 \left[a_p \cos\left(\frac{2\pi pn}{N}\right) + b_p \sin\left(\frac{2\pi pn}{N}\right) \right] \quad (3.5)$$

Using the cutoff frequency as 6 Hz, Fourier coefficients vector is formed as:

$$\mathbf{u}_j^i = (a_0^i, a_1^i, a_2^i, a_3^i, a_4^i, a_5^i, b_1^i, b_2^i, b_3^i, b_4^i, b_5^i)_j^T \quad (3.6)$$

$$\mathbf{u}_k^i = (a_0^i, a_1^i, a_2^i, a_3^i, a_4^i, a_5^i, b_1^i, b_2^i, b_3^i, b_4^i, b_5^i)_k^T$$

where $i = 1, 2, 3, \dots, 700$ stands for the walking trial number and j is the index (j = pelvic tilt, pelvic list or pelvic rotation), k is the joint index (k = hip, knee, or ankle)

3.2.5 Design of GRNNs

Neural network is a highly flexible and nonlinear modeling approach and has been a prevalent analysis tool used in gait studies [105]. In this study, GRNNs were applied to predict the Fourier coefficient vectors when the gait parameters (stride length, cadence) and the lower limb anthropometric data of the subjects are provided as input vectors.

3.2.5.1 Architecture Design of GRNNs

Based on existing literatures [99-102], stride length, cadence, ASIS breadth, thigh length, shank length and foot length were found to be the key factors influencing the lower limb joint angles waveforms. Gait parameters (stride length, cadence) were defined by clinical practitioners while the lower limb anthropometric data of the subject (i.e. ASIS breadth, thigh length, shank length and foot length) were measured by the experimenters.

GRNN is often used as a powerful regression tool because it has a high training speed and a strong non-linear mapping capability [106]. The network consists of an input layer, a radial basis layer and a linear output layer. Each neuron in the hidden

layer has a radial basis function to perform the nonlinear transformation from the input space to the hidden space. The Gaussian function is the common choice for the radial basis neurons and it was introduced in Eq(3-1).

Experimental data of all 700 walking trials (70 participants $\times$ 10 trials/participant) was divided into a training set (600 walking trials) and a test set (100 walking trials). The input vector of the GRNN ($\mathbf{p}_j^i$) consists of gait parameters and anthropometric data. The output vector ($\mathbf{q}_j^i$ or $\mathbf{q}_k^i$) is a Fourier coefficient vector obtain from pelvic angle waveforms and lower limb angle waveforms, respectively. GRNNs were trained with input vectors $\mathbf{p}_j^i$ and output vectors $\mathbf{q}_j^i$ or $\mathbf{q}_k^i$ from the training set. The division of experimental data is shown in Table 3.6. In order to obtain the optimal value of smoothing factors required in the Gaussian function, the GRNNs were trained and tested with smoothing factors vary from 0.01 to 1 at step size 0.01.

Table 3.6: Division of experimental data for GRNNs

	Number of walks	Input vector	Output vector		Predicted by GRNNs	
			Pelvic angles	Lower limb joint angles	Pelvic angles	Lower limb joint angles
Training set	600	$\mathbf{p}_j^i$	$\mathbf{q}_j^i$	$\mathbf{q}_k^i$	$\tilde{\mathbf{q}}_j^i$	$\tilde{\mathbf{q}}_k^i$
Test set	100	$\mathbf{v}_j^i$	$\mathbf{w}_j^i$	$\mathbf{w}_k^i$	$\tilde{\mathbf{w}}_j^i$	$\tilde{\mathbf{w}}_k^i$

3.2.5.2 Smoothing Factor Optimization

The smoothing factor plays an important role in function approximation [106, 108]. A smaller smoothing factor will lead to a 'steeper' radial basis function, so that the neuron with the weight vector closest to the input vector will provide much larger output than other neurons. With an increase in the smoothing factor, the radial basis function's slope becomes smoother and more neurons can respond to an input vector. However, a larger smoothing factor will also make the network function less selective. Therefore, there is a need to determine the optimal smoothing factors for GRNNs. In this study, the optimal smoothing factors were determined by comparing the distances between the prediction and the actual Fourier coefficient vectors in the training set using cross validation. The obtained optimal smoothing factors for GRNN_{Hip}, GRNN_{Knee}, and GRNN_{Ankle} are 25.6, 30.1, and 35.6, respectively.

3.2.6 Assessment Parameters for Gait Pattern Prediction Model

GRNNs were implemented to predict the Fourier coefficient output vectors $\tilde{\mathbf{w}}_j^i$ for the test set (100 walks). Subsequently, the predicted Fourier coefficient vectors $\tilde{\mathbf{w}}_j^i$ were used to reconstruct the lower limb joint angle waveforms by applying the Inverse Fourier Transform in Eq (3.5). In order to assess the quality of gait pattern prediction, comparison was carried out to examine the difference between the predicted angles $\hat{\theta}$ and the actual angles θ . The quality of gait pattern prediction model was evaluated by using three assessment parameters: correlation coefficient ρ , Mean Absolute Deviation (*MAD*) and Threshold Absolute Deviation (*TAD*). The definitions of *MAD* and *TAD* are given as follows:

$$MAD_j = \frac{\sum_{n=0}^{N-1} |\hat{\theta}_{j,n} - \theta_{j,n}|}{N} \quad (3.7)$$

where N is the number of samples in one gait cycle collected from the motion capture experiment, j is the joint index, θ_j are the actual angles of joint j and $\hat{\theta}_j$ are the estimated angles. *MAD* is measured in degree and it determines how much the estimated angles are close to the actual angles

$$TAD_j = \frac{100}{N} \sum_{n=0}^{N-1} T_{j,n} \quad (3.8)$$

$$T_{j,n} = \begin{cases} 1, & \text{when } |\hat{\theta}_{j,n} - \theta_{j,n}| > \gamma \\ 0, & \text{otherwise} \end{cases} \quad (3.9)$$

TAD determines the percentage of points which exceeds a pre-specified threshold around the actual waveform. The pre-specified threshold used here is 5° which is consistent with a previous study [117].

CGA database was often used in gait pattern planning [118]. Normative gait data from Winter[29] is a reliable and popular resource of CGA. The CGA approach was used as a reference to evaluate the proposed model. Since pelvic angle data was not provided in CGA database, only prediction model for lower limb joint waveforms was compared with this reference using the assessment parameters (ρ , *MAD* and *TAD*).

3.2.7 Results

3.2.7.1 Verification of Representing Pelvic Angle Waveforms and Lower Limb Angle Waveforms by Fourier Coefficient Vectors

The reconstructed and actual waveforms of pelvic angle and lower limb joint angle associated with the 700 walking trials are described in Figure 3-10 and Figure 3-11, respectively. The total range of motion of pelvic tilt, pelvic list and pelvic rotation were also calculated and shown in Table 3.7. The results show that reconstructed waveforms using Fourier coefficient vectors closely fit the actual waveforms. In addition, the shape and range of motion of each waveform are in accordance with [110, 119, 120].

Figure 3-10: Actual and reconstructed pelvic angle waveforms with the Fourier coefficient vectors associated with 700 walks (o: actual waveforms, x: reconstructed waveforms)

Figure 3-11: Actual lower limb joint angle waveforms and reconstructed waveforms with the Fourier coefficient vectors associated with 700 walks[98]

Table 3.7: Mean and standard deviation (std) for total range of motion (degrees) of experimental and reconstructed pelvic angle waveforms

	Pelvic Tilt		Pelvic List		Pelvic Rotation	
	Exp	FFT	Exp	FFT	Exp	FFT
Mean	1.4	1.4	7.2	7.2	9.4	9.3
Std	1.0	0.9	1.2	1.2	2.2	2.2

Assessment parameters (ρ , MAD and TAD) were also calculated to measure how close the reconstructed waveforms were to the actual waveforms (Table 3.8). The results show very high correlations (0.99 - 1.00), low MAD ($\leq 0.8^\circ$), and small TAD ($\leq 0.2\%$).

Table 3.8: Mean (Std) of assessment parameters from 700 Walks

	ρ	MAD (Degree)	TAD (%)
Pelvic Tilt	0.99(0.0)	0.08(0.0)	0.0(0.3)
Pelvic List	1.00(0.0)	0.08(0.0)	0.0(0.0)
Pelvic Rotation	1.00(0.0)	0.12(0.1)	0.2(0.7)
Hip	1.00(0.00)	0.0(0.0)	0.0(0.0)
Knee	0.99(0.02)	0.5(0.2)	0.0(0.3)
Ankle	0.98(0.03)	0.8(0.3)	0.1(0.7)

3.2.7.2 Validation of Gait Pattern Prediction Model

The actual and predicted pelvic tilt, pelvic list and pelvic rotation waveforms associated with 100 walking trials are shown from Figure 3-12 to Figure 3-14. Figure 3-15 shows the actual and predicted joint angle waveforms associated with 100 walking trials. The results indicate that the predicted waveforms have similar pattern as the actual waveforms. In general, the average predicted angle waveforms fall within one standard deviation of actual waveforms. Variations from predicted waveforms do not exceed one standard deviation of actual waveforms.

Figure 3-12: Actual and predicted pelvic tilt waveforms associated with 100 walks (Dotted lines- one std of actual waveforms, dashed lines-one std of predicted waveforms)

Figure 3-13: Actual and predicted pelvic tilt waveforms associated with 100 walks

Figure 3-14: Actual and predicted pelvic rotation waveforms associated with 100 walks

Figure 3-15: Actual lower limb joint angle waveforms and predicted waveforms from gait pattern prediction model associated with 100 walks (Dotted lines- one std of actual waveforms, dashed lines-one std of predicted waveforms)[98]

Assessment parameters (ρ , MAD and TAD) were calculated to verify the quality of the gait pattern prediction model. Mean and standard deviation of assessment parameters from 100 walks in test set were calculated and presented in Table 3.9. Assessment parameters for CGA data which provides information of lower limb joint

angles was also calculated for comparison. The results show a good to excellent accuracy of the gait pattern prediction model.

Table 3.9: Mean (Std) of assessment parameters from 100 walks in test set

	ρ		MAD(Degree)		TAD(%)	
	Gait pattern prediction model	CGA from Winter [29]	Gait pattern prediction model	CGA from Winter [29]	Gait pattern prediction model	CGA from Winter [29]
Pelvic Tilt	0.47(0.3)	N/A	0.6(0.3)	N/A	18.0(18.8)	N/A
Pelvic List	0.89(0.1)	N/A	0.8(0.3)	N/A	35.1(21.2)	N/A
Pelvic Rotation	0.90(0.1)	N/A	1.6(0.7)	N/A	28.6(23.2)	N/A
Hip	0.98(0.03)	0.87(0.07)	3.73(1.64)	7.66(1.78)	29.64(23.13)	64.62(14.73)
Knee	0.97(0.04)	0.85(0.11)	5.41(2.01)	9.28(3.07)	44.94(23.19)	62.29(15.21)
Ankle	0.92(0.07)	0.58(0.34)	3.58(1.44)	6.03(1.68)	24.64(20.47)	47.35(16.86)

MAD values highlighted that the average deviation of predicted waveforms from the actual ones ranged from 0.6 degrees to 1.6 degrees for pelvic angle waveforms and from 3.73 degrees to 5.41 degrees for lower limb joint angle waveforms. For CGA, the average value of *MAD* is as high as 9.28 degrees, while the lowest is 6.03 degrees.

When using gait pattern prediction model, the maximum *TAD* (i.e. 44.94%) and minimum *TAD* (i.e. 24.64%) were found for the knee joint and ankle joint, respectively. These values are much lower compared to those from CGA approach, which ranged from 47.35% to 64.62%.

3.2.8 Concluding Remarks

An individual-specific gait pattern prediction model for generating pelvic angle waveforms and lower limb joint angle waveforms of human walking was presented in this work. The model involves two major components. First, FFT was used to simplify the angle waveforms in one gait cycle. The simplification is able to facilitate the analysis process, whereby each waveform in one gait cycle is significantly reduced to eleven Fourier coefficients. Assessment parameters in Table 3.9 show very high correlations (0.99 - 1.00), low *MAD* ($\leq 0.8^\circ$), and small *TAD* ($\leq 0.1\%$) between the reconstructed waveforms and the actual waveforms. The results demonstrated that

the angle waveform can be represented by a Fourier coefficient vector which consisted of eleven elements.

The second component of the proposed subject-specific gait pattern prediction model is the non-linear mapping function which predicts Fourier coefficient vectors from given gait parameters and anthropometric data of any specific subject. The angles waveforms of the pelvic angle waveforms and lower limb joint angle waveforms can be generated from the predicted Fourier coefficient vector by using the inverse Fourier transform Eq(3.5).

The accuracy of the model in predicting gait patterns were assessed by using the correlation coefficient, *MAD* and *TAD*. The assessment parameters showed that gait pattern prediction model was able to generate gait patterns closer to the actual patterns compared to the gait patterns selected from CGA. Specifically, compared to the CGA approach, the proposed prediction model was associated with a higher correlation coefficient, lower *MAD*, and lower *TAD*. These findings support the hypothesis that the proposed model is able to generate a gait pattern better than does the CGA approach in terms of resembling the actual gait pattern of the targeted subject.

Individual factors, such as individual anthropometric dimensions, were taken into account when developing the model. Thus, a strength of the proposed model is that it is individual specific and able to address inter-individual differences.

In robotics gait rehabilitation, different walking speeds used in the robotics systems may be required at different stages of the training process. For example, slow walking speeds are usually used for training at the beginning stage. When the condition is improved, faster walking speeds are applied to provide a better therapeutic outcome. Walking speed is one of the key factors that influence the walking gait pattern [101, 102]. Therefore, when different walking speeds are required for the training purpose, suitable gait patterns must be planned for the robotics systems. The walking speeds can be related to gait parameters (stride length, cadence). Since gait parameters are included in the input vectors of the GRNNs, the proposed model can be implemented to plan different gait patterns at different walking speeds.

From the clinical aspect of gait rehabilitation, functional recovery is maximized when locomotor training follows three major principles: practice, specificity and

effort [121, 122]. The first two principles emphasize that inducing correct joint kinematics to a patient in a repetitive manner results in better therapeutic outcomes and more practicing leads to improved motor learning. Therefore, it's important to plan correct motions for robotic trainers given that the patients will learn the gait pattern imposed to them during training process. It has been shown that variability in gait patterns are associated with differences in anatomical properties and walking speeds [100, 123-126]. The present model is able to plan correct gait patterns in robotic gait rehabilitation by considering inter-subject difference and variability in walking speed. Thus, it can improve the therapeutic outcomes and help patients regain functional capacity.

A gait pattern prediction model and its applicability have been introduced. Some limitations and future directions will be discussed in next paragraphs to further improve the model. At a general level, the physical conditions of subjects with gait deficit can be divided into symmetric and asymmetric gait conditions. If the patients exhibit frozen joint or physical constraint that prevent the lower limb joints from achieving normal range of motion, they will belong to asymmetric condition. The joint kinematics of left and right legs are significantly different in this condition. The present model has not tailored to this group of patients in the current stage. Another limitation of this model is that it does not deal with asymmetries in anthropometric data of an individual.

GRNNs were implemented as non-linear mapping functions in the present model and the results are promising. However, neural network can only implicitly learn the distribution function of the observed data and the effect of each anthropometric factor on gait pattern has not been shown. An explicit regression function may further improve the present model.

The current model was trained and verified using the gait data from healthy younger subjects. However, gait rehabilitation is more common among older adults. The proposed gait pattern prediction model is independent of the subject population. Therefore, if the gait data from healthy older adults is available for the training of the GRNNs, we believe that the proposed model is also able to accurately help generate gait patterns for gait rehabilitation among older adults.

Chapter 4

COORDINATING FOR NATURAL GAIT-LIKE WALKING AND PLAYBACK ON ROBOTIC GAIT REHABILITATION SYSTEMS

Existing research mainly used Clinical Gait Analysis (CGA) data as the reference in their gait pattern planning [18, 25-28]. Normative gait data from Winter [29] is a reliable and popular resource of CGA. The CGA data was obtained using the motion capture system. Thus, using CGA data in the robotic systems may not provide a natural gait-like walking pattern due to the inherent errors (e.g. marker placement error, soft-tissue error) caused by the motion capture system and difference in anthropometric data of different subjects. This chapter will discuss about adjusting the gait pattern from motion capture data to 1) obtain a correct coordination between pelvic and lower limb movement and synchronization between pelvic center movement in the line of progression and progression velocity for over-ground gait trainers which consist of pelvic assistance and robotic orthosis, *NaTure-gaits*, and 2) improve the foot contact of automated gait trainers. This work is also the third stage of *GaitGen* model introduced in Chapter 3 which works on translating and coordinating the gait pattern for gait locomotion playback on robotic gait rehabilitation system.

4.1 Motion Capture System and Marker Placement

Modeling the human body as a series of interconnected body segments is a standard biomechanical approach [127, 128]. When studying the movements of a segment in 3D-space, relative positions and orientations of that segment must be considered. Several practical methods have been used to obtain relative orientations of body segments either directly or indirectly. For examples, electrogoniometers [129-132] have been used to directly measure the 3D joint rotation of lower extremity. Accelerometers have also been used for indirect measurement of lower limb joint angles [133, 134]. Vicon system from Oxford Metrics [29, 114, 128] is a modern computer- and video-based biomechanical analysis system which has been widely

used to obtain accurate 3D spatial positions of reflective markers placed on the body segments.

A marker system which determined where on the lower extremities the markers should be placed was required before carrying motion capture experiments. Helen Hayes Hospital marker set has been widely accepted in biomechanical analysis [29, 114]. In Helen Hayes model, the movement of pelvic segment is described through a pelvic anatomical coordinate system which is defined by use of surface markers place on the right and left anterior superior iliac spines (RASIS and LASIS) and the Sacrum or also referred as the midpoint between the right and left posterior superior iliac spines (RPASIS and LPSIS). Details of the three markers (RASIS, LASIS, and Sacrum) which define the position of pelvis in 3D space and a pelvic anatomical coordinate system uvw are illustrated in Figure 4-1.

Figure 4-1: The three markers (RASIS, LASIS, and Sacrum): a) lateral view, b) anterior view. The uvw reference system may be used to estimate the positions of the right and left hip

The origin of reference coordinate system uvw for the pelvis is placed at Sacrum. The v axis is parallel to the line between RASIS and LASIS marker. The w axis is perpendicular to the plane that formed by the three markers (RASIS, LASIS, and Sacrum). Finally, the u axis is at right angles to both v and w so that the three axes

$\mathbf{uvw}$ form a right-handed system. The unit vectors of $\mathbf{uvw}$ system are defined as follows:

$$\mathbf{v}_{Pelvis} = \frac{(\mathbf{r}_{LASIS} - \mathbf{r}_{RASIS})}{|\mathbf{r}_{LASIS} - \mathbf{r}_{RASIS}|} \quad (4.1)$$

$$\mathbf{w}_{Pelvis} = \frac{(\mathbf{r}_{RASIS} - \mathbf{r}_{Sacrum}) \times (\mathbf{r}_{LASIS} - \mathbf{r}_{Sacrum})}{|(\mathbf{r}_{RASIS} - \mathbf{r}_{Sacrum}) \times (\mathbf{r}_{LASIS} - \mathbf{r}_{Sacrum})|} \quad (4.2)$$

$$\mathbf{u}_{Pelvis} = \mathbf{v}_{Pelvis} \times \mathbf{w}_{Pelvis} \quad (4.3)$$

where $\mathbf{r}_{RASIS}$, $\mathbf{r}_{LASIS}$, and $\mathbf{r}_{Sacrum}$ is the positions of RASIS, LASIS and Sacrum marker in global coordinate $\mathbf{OXYZ}$, respectively.

4.2 Estimation of Hip Joint Centers

One of the problems in capturing kinematic data is that we are really interested in the position of the underlying skeleton, but we are only able to measure the positions of external landmarks. The position of non-palpable (internal) anatomical landmarks (AL) is generally reconstructed using indirect methods. Among the internal ALs, the hip joint center (HJC), is particularly important in that it is used to define the femoral anatomical coordinate system. Moreover, in view of biomechanical model of human body, HJCs is the points that connect the pelvis to the lower extremities. Study from Stagniet *et al*[135] revealed that inaccuracies in HJC estimates affect both angles and moments at the hip and knee joint. Hip moment appeared to be the most sensitive to the HJC location errors: a 30 mm HJC anterior mislocation resulted in a propagated error of about -22%.

The HJC positions could be estimated by using the function approach, i.e., as the mean center of 3D rotation of the thigh relative to the pelvis [128, 136] or by using regression equations with independent variables that determine the geometry of the pelvis [114, 137-141]. The functional approach provided a better accuracy in HJC estimation than the latter method. However, this method was time consuming since the subjects could be required to perform full range of motion at their hip joints to collect the data for calibration. The regression equations as in (4.4) estimate HJC in global coordinate $\mathbf{OXYZ}$ from Sacrum position, ASIS breadth, and pelvic anatomical coordinate $\mathbf{uvw}$ [114]. Details of HJC positions, external landmarks and coordinates are illustrated in Figure 4-2.

$$\begin{aligned} \mathbf{r}_{RHJC} &= \mathbf{r}_{Sacrum} + 0.598w_{ASIS}\mathbf{u}_{Pelvis} - 0.344w_{ASIS}\mathbf{v}_{Pelvis} - 0.290w_{ASIS}\mathbf{w}_{Pelvis} \\ \mathbf{r}_{LHJC} &= \mathbf{r}_{Sacrum} + 0.598w_{ASIS}\mathbf{u}_{Pelvis} + 0.344w_{ASIS}\mathbf{v}_{Pelvis} - 0.290w_{ASIS}\mathbf{w}_{Pelvis} \end{aligned} \quad (4.4)$$

where $\mathbf{r}_{RHJC}$ and $\mathbf{r}_{LHJC}$ is the right and left HJC, respectively. w_{ASIS} is ASIS width.

Figure 4-2: The pelvic model and hip joint center in global coordinate

The pelvic segment and its reference coordinate $\mathbf{uvw}$ could be determined by the three markers at RASIS, LASIS and Sacrum as in Eq(4.4). Alternatively, pelvic segment can be defined by Sacrum position and three rotational movements: pelvic tilt, pelvic list and pelvic rotation as introduced in Section 3.2.2. In this scenario, HJCs in global coordinate $\mathbf{OXYZ}$ are calculated using transformation matrix method as follows:

$$\mathbf{r}_{HJC} = \mathbf{T}_O^P \cdot \mathbf{p}_{HJC} \quad (4.5)$$

where $\mathbf{T}_O^P$ is transformation matrix from global coordinate $\mathbf{OXYZ}$ to pelvic reference coordinate $\mathbf{uvw}$ and $\mathbf{p}_{HJC}$ is position of HJC in $\mathbf{uvw}$ coordinate

The transformation matrix can be decomposed into two parts:

$$\mathbf{T}_O^P = \begin{bmatrix} \mathbf{R}_O^P & \mathbf{r}_{Sacrum} \\ 0 & 1 \end{bmatrix} \quad (4.6)$$

where $\mathbf{R}_O^P \in \mathbf{R}^{3 \times 3}$ is the rotation of $\mathbf{uvw}$ frame with respect to global coordinate $\mathbf{OXYZ}$ and $\mathbf{r}_{\text{Sacrum}}$ is the translation of $\mathbf{uvw}$ origin in global coordinate

The rotation matrix is given as follows:

$$\mathbf{R}_O^P = \mathbf{R}_Z(\theta_3) \mathbf{R}_Y(\theta_2) \mathbf{R}_X(\theta_1) \quad (4.7)$$

4.3 Coordination between Pelvic Assistance and Robotic Orthosis

Details of *NaTure-gaits* and its three modules: Pelvis Assistance (PA), Robotic Orthosis (RO) and Mobile Platform (MP) were introduced in Chapter 5. The PA mechanism has a pair of robotic arms which hold the subject at both sides of the pelvis through a harness device. Figure 4-3 shows the model of PA mechanism with human's lower extremities. Movement of end effector should be carefully defined because this position is the contact point and support position between human and machine. Moreover, natural gait-like trajectory planning for the end effector is required for the coordination of PA and RO mechanism because it is the interconnected point of the two modules.

Figure 4-3: Illustration of pelvic motion provision by the pelvic assistance mechanism

Positions of end effectors could be calculated from the positions of HJCs which were derived from (4.4). The computed HJC trajectories could be used to determine the effector positions as follows:

$$\begin{aligned}
\mathbf{r}_{Hip} &= \frac{\mathbf{r}_{LHJC} - \mathbf{r}_{RHJC}}{|\mathbf{r}_{LHJC} - \mathbf{r}_{RHJC}|} \\
\mathbf{r}_{PA,r} &= \mathbf{r}_{RHJC} - \frac{B_w - |\mathbf{r}_{LHJC} - \mathbf{r}_{RHJC}|}{2} \mathbf{r}_{Hip} \\
\mathbf{r}_{PA,l} &= \mathbf{r}_{LHJC} + \frac{B_w - |\mathbf{r}_{LHJC} - \mathbf{r}_{RHJC}|}{2} \mathbf{r}_{Hip}
\end{aligned} \tag{4.8}$$

where $\mathbf{r}_{Hip}$ is the unit vector with the direction from RHJC to LHJC. $\mathbf{r}_{PA,r}$ and $\mathbf{r}_{PA,l}$ are vectors determines position of right and left end effector in global coordinate **OXYZ**, respectively. B_w is the waist breadth of the subject

The orientation and position of pelvic relative to the global coordinate **OXYZ** could be generated by controlling the position of the two end effectors of the PA mechanism, which are given by:

$$\theta_{tilt} = \tan^{-1} \left(\frac{Z_{PA,l} - Z_{PA,r}}{Y_{PA,l} - Y_{PA,r}} \right) \tag{4.9}$$

$$\theta_{rot} = \tan^{-1} \left(\frac{Y_{PA,l} - Y_{PA,r}}{X_{PA,l} - X_{PA,r}} \right)$$

$$\mathbf{r}_{Pelvis} = \frac{1}{2} \begin{bmatrix} \mathbf{X}_{PA,r} + \mathbf{X}_{PA,l} \\ \mathbf{Y}_{PA,r} + \mathbf{Y}_{PA,l} \\ \mathbf{Z}_{PA,r} + \mathbf{Z}_{PA,l} \end{bmatrix} \tag{4.10}$$

where θ_{tilt} and θ_{rot} are the angle of pelvic tilt and pelvic rotation, respectively. $\mathbf{r}_{Pelvis}$ the pelvic position.

Figure 4-4: Trajectories of hip joint center (dotted line) and contact point (solid line) of the left side in one walking gait cycle

4.4 Synchronization between Pelvic Assistance and Mobile Platform

Calculation of hip joint center and end point position of Pelvic Assistance (PA) mechanism was introduced in Section 4.3. End point position of PA in one gait cycle during human walking in sagittal plane was calculated and shown in Figure 4-5. Average walking velocity in progression direction could be determined from the distance travel in one gait cycle time as follows:

$$\dot{X}_{PA,r} = \frac{X_{PA,r}(N) - X_{PA,r}(0)}{T} \quad (4.11)$$

where

$\dot{X}_{PA,r}$: Average walking velocity of pelvic movement in progression direction or x -axis.

$X_{PA,r}(N)$ and $X_{PA,r}(0)$ are right end effector position of PA at 100% gait cycle and 0% gait cycle, respectively.

T is the time taken to complete one gait cycle

Figure 4-5: Human walking in sagittal plane

The pelvic trajectories during human walking in progression direction can be decomposed into a constant velocity movement at $\dot{X}_{PA,r}$ speed and a localized pelvic motion. The conversion of pelvic motion in progression direction is illustrated as follows:

Figure 4-6: Conversion from pelvic motion to motion for mobile platform and pelvic assistance mechanism

In *NaTure-gaits* system, the constant velocity movement in progression plane was accomplished by a two wheel Mobile Platform. The position of mobile platform is given by:

$$X_{MP} = \dot{X}_{PA,r} \times t_{GC} \quad (4.12)$$

where t_{GC} is the instant within one gait cycle, $0 \leq t_{GC} \leq T$

Localized pelvic motion in progression direction is calculated as follows:

$$x_{PA,r} = X_{PA,r} - X_{MP} \quad (4.13)$$

Similarly, localized pelvic motion in y-axis and z-axis were also analyzed and they can be calculated as follows:

$$\begin{aligned} y_{PA,r} &= Y_{PA,r} - \bar{Y}_{PA,r} \\ z_{PA,r} &= Z_{PA,r} - Z_{Hip} \end{aligned} \quad (4.14)$$

where Z_{Hip} is the hip coordination in z -axis when subject at standing position

The motion planning for left end effector was calculated from the right end effector with 50% phase lag. The motion of the pelvis in the z -axis is found to be always lower than the hip height of standing. Final trajectories of pelvic motion for play-back on PA mechanism of *NaTure-gaits* are illustrated as follows:

Figure 4-7: Final constructed motion for PA mechanism in the direction of x -axis
(Solid line – right side, dotted line – left side)

Figure 4-8: Final constructed motion for PA mechanism in the direction of y -axis
(Solid line – right side, dotted line – left side)

Figure 4-9: Final constructed motion for PA mechanism in the direction of z -axis
(Solid line – right side, dotted line – left side)

Localized movement of PA mechanism in 3D space was also analyzed and shown in Figure 4-10. Left and right end effectors of PA mechanism have the same trajectory in sagittal plane. In frontal plane, the trajectories have figure “8”. The results were agreed with previous pelvic motion study in [110].

Figure 4-10: Final constructed motion for PA mechanism in 3D space
(Solid line – right side, dotted line – left side)

4.5 An Optimization Model for Improving Foot Contact in the Robotic Gait Rehabilitation System

A basic walking cycle can be divided into two phases: stance phase and swing phase. Stance phase begins with initial foot contact and represents roughly 62% of the gait cycle [110]. During stance phase, the entire body weight is either supported by two feet contact with the floor (double limb stance) or just by one foot on the floor (single limb support). The duration of single limb support is a useful index to measure the limb's support capability [109].

Foot contact during stance phase of normal walking plays an important role in locomotor functions. Foot mechanism and ankle mechanism were reported to be two of the six determinants of walking gait [109]. Providing physiological resembling walking motion was reported to be important in robotic assisted gait rehabilitation training process [58]. Thus, it is crucial that the motion performed by the robotic systems mimics the foot contact pattern of normal human walking.

Existing research mainly used Clinical Gait Analysis (CGA) data as the reference in their gait pattern planning for robotic gait rehabilitation systems [18, 25-28]. Normative gait data from Winter [29] is a reliable and popular resource of CGA. The

CGA data was obtained using the motion capture system. Thus, using CGA data in the robotic system may not provide desired foot contact due to the inherent errors (e.g. marker placement error, soft-tissue error) caused by the motion capture system. To ensure the robotic system walking with desired foot contact, adjustment of motion capture data is required.

This work aims to develop an optimization model for proper foot contact in robotic assisted gait rehabilitation systems. Motion capture experiments of human walking were carried out to collect pelvic and lower limb kinematic data. Subsequently, foot contact represented by heel trajectory and foot-to-ground angle was calculated by using lower limb kinematics. An optimization model using the Generic Algorithm (GA) was applied to adjust the lower limb joints angles for a better foot contact. The proposed model was required to maintain the smoothness of heel trajectory, foot-to-ground angles and lower limb joints angles after the adjustment process. Initial trials with an over-ground gait trainer (i.e. *NaTure-gaits*) were conducted and vertical ground reaction force (vGRF) was collected to evaluate the effectiveness of the proposed model. We hypothesized that the proposed model would be able to provide a better foot contact and realistic walking for the target subject on robotic training devices.

4.5.1 An Optimization Model for Improving Foot Contact

The optimization model for improving foot contact in robotic assisted gait rehabilitation is illustrated in Figure 4-11. Kinematic model of the lower extremity was implemented to calculate heel trajectory and foot-to-ground angles given pelvic trajectory and lower limb joints angles. Subsequently, the GA was applied to optimize the foot contact during the stance phase if the heel trajectory and foot-to-ground angles do not satisfy the physical requirements of foot contact during walking (the physical requirements are given below). In this work, the lower limb kinematics was analyzed in the sagittal plane (flexion-extension) only. Hip, knee, and ankle joint angles were modified during the optimization process to achieve a better foot contact.

Figure 4-11: The optimization model for improving foot contact in robotic assisted gait rehabilitation

4.5.2 Lower Limb Kinematics of Human Walking

The lower limb of human walking in the sagittal plane is illustrated in Figure 4-12. **OXZ** is the global coordinate. The hip, knee and ankle joint angles are respectively represented by $\theta_h, \theta_k, \theta_a$. Positive values indicate flexion (or dorsiflexion) and negative values indicate extension (or plantarflexion). Foot-to-ground angle θ_f indicates the orientation of foot with respect to the ground surface. Foot-to-ground angle is positive when metatarsal head II is higher than heel. Thigh length and calf length are defined as l_t and l_s , respectively. Heel position can be defined relative to the ankle joint by malleolus height l_h and l_f .

Figure 4-12: The lower limb model of human walking in sagittal plane

After segment reference frame in each lower limb segment was constructed, a transformation matrix from global frame to foot reference frame can be defined. Subsequently, given hip trajectory and lower limb joint angles, heel trajectory and foot-to-ground angle can be calculated as follows:

$$\begin{aligned}
 \mathbf{X}_{heel} &= l_h \sin(\theta_h - \theta_k + \theta_a) + l_f \cos(\theta_h - \theta_k + \theta_a) + \mathbf{X}_{hip} + l_t \sin(\theta_h) + l_s \sin(\theta_h - \theta_k) \\
 \mathbf{Z}_{heel} &= -l_h \cos(\theta_h - \theta_k + \theta_a) + l_f \sin(\theta_h - \theta_k + \theta_a) + \mathbf{Z}_{hip} - l_t \cos(\theta_h) - l_s \cos(\theta_h - \theta_k) \\
 \theta_f &= \theta_h - \theta_k + \theta_a
 \end{aligned} \tag{4.15}$$

4.5.3 Foot Contact during Human Walking

Based on existing kinematic analysis of human walking [109, 110, 114], the physical requirements for foot contact during one walking gait cycle are as follows:

- Heel position in the Z direction is zero or at ground level between heel strike (0% of GC) and heel off (48% of GC).
- Foot-to-ground angle during foot flat (12% of GC) to heel off (48% of GC) period is zero degree.

To illustrate the improper foot contact due to inherent errors during motion capture experiment, heel trajectories and foot-to-ground angles were computed using

lower limb kinematics with lower limb lengths and lower limb joints angles obtained from Clinical Gait Analysis (CGA) [29]. The results were showed in Figure 4-13.

Figure 4-13: Heel position in the vertical direction Z (dotted line) and foot-to-ground angles (solid line) with data obtained from CGA [29]

Figure 4-13 showed that the heel positions in vertical direction were below the ground level and they were not at the same level during heel strike to heel off period. The results of foot-to-ground angles demonstrated that the metatarsal head II was lower than the heel (negative values) during foot flat to heel off period. Improper foot contact may reduce the capability of single limb support during stance phase and they are not feasible in normal human walking.

4.5.4 An Optimization Model for Improving Foot Contact using Generic Algorithm

The previous section highlighted the need to adjust the walking motion data obtained from motion capture experiment for proper foot contact before be implemented on rehabilitation system with robotic orthosis module.

An optimization model was developed to improve foot contact by modifying lower limb joints angles. The proposed model aims 1) to keep the heel position in vertical direction, Z, at ground level during heel strike to heel off period, 2) to shift the foot-to-ground angles to zero during foot flat to heel off period, and 3) To

preserve the smoothness of heel trajectory, foot-to-ground angles and lower limb joints angles.

Based on Eq (4.15), the heel position in vertical direction, Z , can be computed as follows:

$$\mathbf{Z}_{heel} = \mathbf{Z}_{hip} - l_t \cos(\theta_h) - l_s \cos(\theta_h - \theta_k) - l_h \cos(\theta_h - \theta_k + \theta_a) + l_f \sin(\theta_h - \theta_k + \theta_a) \quad (4.16)$$

$$\mathbf{Z}_{heel}^* = \mathbf{Z}_{hip} - l_t \cos(\theta_h') - l_s \cos(\theta_h' - \theta_k') - l_h \cos(\theta_h' - \theta_k' + \theta_a') + l_f \sin(\theta_h' - \theta_k' + \theta_a') \quad (4.17)$$

where $\theta_h' = \theta_h + \Delta\theta_h$, $\theta_k' = \theta_k + \Delta\theta_k$, and $\theta_a' = \theta_a + \Delta\theta_a$ are the hip, knee and ankle joints angles after adjustment, respectively.

Heel position was maintained at the same level during heel strike to heel off period by minimizing the objective function given as:

$$f(\Delta\theta_h, \Delta\theta_k, \Delta\theta_a) = \frac{1}{HO} \sum_{n=0}^{HO} (\mathbf{Z}_{heel}^*(n) - \mathbf{Z}_{heel,min})^2 \quad (4.18)$$

where HO is the instance of heel off that are measured in percentage of one gait cycle and $\mathbf{Z}_{heel,min}$ is the lowest heel position in Z -axis before adjustment. Subsequently, the whole lower limb trajectories would be shifted in the Z -direction to move heel strike position to the ground level.

Foot-to-ground angle waveform was offset so that the angles during the foot flat to heel off phase close to zero. The foot-to-ground angles can be computed as follows:

$$\begin{aligned} \theta_f &= \theta_h - \theta_k + \theta_a \\ \theta_f^* &= \theta_f - \theta_{f,min} \end{aligned} \quad (4.19)$$

where θ_f^* is the angle with adjustment and $\theta_{f,min}$ is the smallest angle in foot flat to heel off period.

Therefore, the adjustment values of lower limb joints angles were constrained as follows:

$$\Delta\theta_h - \Delta\theta_k + \Delta\theta_a = -\theta_{f,min} \quad (4.20)$$

The second constraint is the physical limitation of hip, knee, and ankle joints' range of motion during normal walking which can be found from existing literature [109, 110]. The limit of hip, knee, and ankle joints range of motion was set as:

$$\begin{aligned}
-10^\circ &\leq \theta_h \leq 30^\circ \\
2^\circ &\leq \theta_k \leq 70^\circ \\
-20^\circ &\leq \theta_a \leq 10^\circ
\end{aligned} \tag{4.21}$$

The proposed adjustment model contained one objective function to be optimized and two constrained functions. The GA, which is a tool that can be used to solve both constrained and unconstrained optimization problems based on natural selection, was utilized to search for adjustment values of hip, knee, and ankle angles. In this work, the GA was implemented using global optimization toolbox of Matlab (The MathWork Inc., Natick, MA).

4.5.5 Assessment Parameters for the Optimization Model

Optimization model for improving foot contact was implemented to improve the foot contact during human walking. In order to assess the quality of the proposed model, mean absolute errors were calculated to examine the difference between the original and the adjusted foot contact. The definition of mean absolute error for heel positions and foot-to-ground angles are given as follows:

$$\begin{aligned}
\bar{e}_{heel} &= \frac{1}{N} \sum_{n=0}^{HO} \frac{|Z_{heel}(n)|}{HO+1} \\
\bar{e}_f &= \frac{1}{N} \sum_{n=FF}^{HO} \frac{|\theta_f(n)|}{HO-FF+1}
\end{aligned} \tag{4.22}$$

where $N=8$ is the number of subjects in motion capture experiment, FF and HO are the instance of foot flat and heel off, respectively.

Clinical-based assessment parameter, specifically vertical ground reaction force (vGRF) was used to evaluate the effectiveness of the proposed model. It has been known that sufficient ground reaction forces (GRF) that support the body play a crucial role during human walking. GRF and periodic movement of each foot are the two basic requisites of human walking [114]. Transient loading of the limb was able to enhance the activity in antigravity muscles during stance and delays the onset of the next flexion [142].

An over-ground gait trainer, *NaTure-gaits* (**N**atural and **T**une-able **r**ehabilitation **g**ait system) was used to playback the original gait pattern obtained from motion capture experiment and the adjusted gait pattern. Details of *NaTure-gaits* and its modules could also be found in [143]. vGRF when the subjects walking with *NaTure-gaits* using original gait pattern and adjusted gait pattern were measured for

comparisons. In this study, a wearable force system was developed to measure vGRF. The system included flexi-force sensors (Tekscan, Inc. USA) and a wireless data acquisition device (NI-WLS 9163) from National Instruments. A total of five flexi-force sensors were attached at the heel, first metatarsal, third metatarsal, fifth metatarsal and big toe, respectively. The subject was instructed to finish 10-meter walks under three conditions: normal walking, walking with *NaTure-gaits* using original gait pattern and walking with *NaTure-gaits* using adjusted gait pattern. The experimental setup is illustrated as follows:

Figure 4-14: An experiment for vertical force data collection (a) normal walking, (b) walking with *NaTure-gaits*

4.5.6 Results

Heel positions in vertical direction and foot-to-ground angles of eight subjects were calculated. Subsequently, mean absolute errors and standard deviation were also calculated to measure how close the original and adjusted foot contacts were to the proper foot contact (Table 4.1). The results show that heel position error and its deviation $\bar{e}_{heel}(std)$ from eight subjects decreased from 37.4(30.9) to 10.3(3.7) after adjustment. The adjustment procedure also helped to reduce the errors of foot-to-ground angles $\bar{e}_f(std)$ from 3.5(2.5) to 1.6(0.9).

Table 4.1: Mean (Std) of assessment parameters from 8 subjects

$\bar{e}_{heel}^{(std)}$, mm		$\bar{e}_f^{(std)}$, degrees	
Original foot contact	Adjusted foot contact	Original foot contact	Adjusted foot contact
37.4(30.9)	10.3(3.7)	3.5(2.5)	1.6(0.9)

Effectiveness of the proposed model in term of clinical assessment was also evaluated via vertical ground reaction force (vGRF). The results of vGRF for both right and left legs in one gait cycle were calculated for three conditions: self-paced normal walking speed, walking with *NaTure-gaits* using original gait pattern, and walking with *NaTure-gaits* using adjusted gait (Figure 4-15).To quantify the vGRF patterns, four parameters including first peak, second peak, duration of single support, and duration of double support were used. In general, the first peak and second peak occurs at heel contact and push-off, respectively. Duration of single support was defined as the interval between heel strike and toe-off of the same foot and duration of double support was defined as the interval between heel-strike of one foot and toe-off of the other foot. These parameters have been used extensively in previous human gait research [110, 144, 145]. The parameters were calculated and showed in Table 4.2.

Figure 4-15: Vertical ground reaction forces, vGRF (solide line: normal walking, dotted line: walking with *NaTure-gaits* using adjusted gait pattern and dashed line: walking with *NaTure-gait*, original gait pattern)

Table 4.2: Quantify parameters of vertical ground reaction force (vGRF)

vGRF	First peak (N)	Second peak (N)	Single Support (% gait cycle)	Double Support (% gait cycle)
Walking without <i>NaTure-gaits</i>	495	816	39.5	22.5
Walking with <i>NaTure-gaits</i> , original gait pattern	0	48.8	35.4	0
Walking with <i>NaTure-gaits</i> , adjusted gait pattern	324.3	195.3	42.4	19.6

4.5.7 Discussions

An optimization model for improving foot contact has been proposed. Better heel trajectories and foot-to-ground angles during stance phase were achieved by adjusting the three lower limb joints angles (i.e. ankle, knee, and hip). The model also aimed to preserve the smoothness of lower limb motion and three constraints have been imposed to ensure that the adjustment of the angles does not exceed physiologically permitted range of motion.

Results from Table 4.1 revealed that the optimization model for proper foot contact created a reduction of 72.5% and 54.3% for $\bar{e}_{heel}$ and $\bar{e}_f$, respectively. In addition, the standard deviation of $\bar{e}_{heel}$ and $\bar{e}_f$ were significantly reduced by about 88% and 64%. The results confirmed that foot contact when using *NaTure-gaits* with adjustment of gait pattern was improved compare to using *NaTure-gaits* with original gait pattern. However, it is important to note that the proposed model did not diminish $\bar{e}_{heel}$ and $\bar{e}_f$ values for an ideal foot contact during human walking. Theoretically, heel position must stay on the ground during heel strike to heel off and foot-to-ground angle remains zero from foot flat to heel off. Nevertheless, mathematically adjusting $\bar{e}_{heel}$ and $\bar{e}_f$ values to zero would disrupt the smoothness of the lower limb joints angles. In this work, the third constraint of the adjustment model was to preserve the smoothness of motion, because human walking shall be carried out smoothly.

Figure 4-15 showed a typical pattern of vGRF when the subject was instructed to walk at self-paced normal walking speed without *NaTure-gaits*. It was found that vGRF of normal walking increase in weight acceptance, decrease through mid-stance

and increase again to the second peak at push-off. The result was agreed with the previous studies [110, 144-146].

A poor vGRF pattern was shown when the subject was walking with *NaTure-gaits* using original gait pattern (Figure 4-15 and Table 4.2). For example, the magnitude of this vGRF pattern was very low and the value of vGRF at heel strike was zero. Duration of single support was reduced to 35.4% of the gait cycle and double support time was missing in this case. Shorter stance time and decrease in ground reaction forces have been reported to be related with pathological gait [147, 148]. In general, the vGRF pattern became closer to the normal vGRF pattern when the gait pattern was adjusted and implemented in *NaTure-gaits* (Figure 4-15). Four parameters that quantify the vGRF pattern were improved (Table 4.2) after the gait pattern adjustment. The improvement of vGRF pattern when using the adjusted gait pattern has confirmed the effectiveness of the optimization model for proper foot contact in term of clinical gait assessment in rehabilitation.

The current model utilized the generic algorithm to optimize the foot contact of a subject when walking with robotic assisted system. The searching algorithm was time consuming and therefore the model has only been used in offline mode to improve foot contact for pre-defined gait pattern. A model that provides correct foot contact in real time during the gait training process may be needed.

In summary, an optimization model for proper foot contact has been proposed and tested on an over-ground gait training system, *NaTure-gaits*. It has been shown that by modifying lower limb joints angles, the foot contact can be improved compared to the original motion.

Chapter 5

DESIGN A CONTROL MODULE FOR AN OVER-GROUND GAIT REHABILITATION SYSTEM: *NATURe-GAITS*

Therapist assisted body weight supported (TABWS) gait rehabilitation was introduced two decades ago and its benefit in functional improvement in walking ability for SCI and stroke patients has been demonstrated. However, shortage of therapists, labor-intensiveness, and short duration of training time are some limitations of this approach. To overcome these deficiencies, robotic assisted gait rehabilitation systems were developed and they have gained attentions from researchers and clinical practitioner in recent years. An over-ground gait rehabilitation system, *NaTure-gaits*, has been developed by Lim *et al*[149] in Nanyang Technological University, Singapore. This chapter introduces the design of mechanical structure of *NaTure-gaits* as well as electrical and controller hardware used in the system. The design was based on clinical approach to provide four main features which are pelvic motion, body weight support, over-ground walking experience and lower limb assistance. These features were achieved by three main modules of *NaTure-gaits*: Pelvic assistance mechanism (PA), mobile platform (MP) and robotic orthosis (RO). The gait system has been tested on subjects and preliminarily assessed by therapists and doctors. The results showed that the system is able to perform ten meters walk with the great reduction in man power and the subjects felt comfortable with the induced gait patterns.

5.1 Clinical-based Approaches for the Design of *NaTure-gaits*

Motor learning of neurological injury rehabilitation relies on three principles: practice, specificity, and effort [10, 45]. With all other things being equal, more practice will result in more learning [46]. The clear benefits of intensive repetitive therapy have been demonstrated by Kwakkel *et al*. [47]. Specificity is the second principle, which highlights that the best way to improve performance of a motor task is to execute that specific motor task [48]. The importance of task specificity in gait

rehabilitation has been highlighted in reference [21]. The last principle, effort, indicates that a high degree of participation and involvement of individuals is required to facilitate motor learning [49, 50].

To fulfil the first two principles, four features which are pelvic assistance, body weight support, over ground mobility and lower limb assistance were defined as guidelines for the design of the system. The third principle could be achieved by an assist as needed control strategy after the prototype of the system was available. The details of these features are as follows:

➤ **Pelvic Motion**

Unrestricted pelvic movement plays an important role in normal locomotion and thus it is included as one of the essential features in this work

Promote body weight shifting during gait rehabilitation

➤ **Body Weight Support**

Unique body weight support approach, without the restriction of pelvic movement

➤ **Over Ground Mobility**

Practicing gait in functional over-ground walking, as opposed to treadmills

➤ **Reciprocal Stepping of Lower Limb**

Assists motion of hip, knee and ankle in sagittal plane, providing actual functional over-ground walking.

Each of the proposed features can be achieved by a module on the robotic system. These modules need to synchronize together throughout the operation to achieve the desired gait locomotion. In order to provide over-ground walking, a mobile platform (MP) is incorporated in the system. The mobile platform follows the patient during gait rehabilitation and it carries all other modules with it. A pair of robotic arms for Pelvic Assistance (PA) mechanism is attached on the mobile platform. The end (end effector) of the arm connects to the waist of patient, to provide BWS and pelvic control. Lastly, a lower limb robotic orthosis (RO) is attached to the end of the parallelogram arm, which induces gait locomotion to the patient during training. The

conceptual idea of the modules contained in the robotic gait rehabilitation system is shown in Figure 5-1.

Figure 5-1: A conceptual idea of the gait rehabilitation methodology and its realization

5.2 Prototype of *NaTure-gaits* and Its Modules

The robotic system named as *NaTure-gaits* (*Natural and tune-able rehabilitation gait system*). It was designed to allow natural and tune-able gait locomotion during rehabilitation. The overview of *NaTure-gaits* and its modules are shown in Figure 5-2. *NaTure-gaits* is designed to fit different size of human subjects with the anthropometric data as listed in Table 5.1.

Figure 5-2: Assembled prototype of *NaTure-gaits* and the three main modules (PA: Pelvic Assistance, MP: Mobile Platform and RO: Robotic Orthosis)

Table 5.1: Anthropometric data of targeted users

	Minimum	Maximum
Body Weight	-	80kg
Waist Height	840 mm	1000 mm
Shank Length	330 mm	400 mm
Thigh Length	330 mm	400 mm
Hip Breadth	250 mm	550 mm

5.2.1 Pelvic Assistance Mechanism (PA) –Mechanism Design and Kinematic model

In general, pelvis can be modeled as a body with six DoFs, which consists of translational and rotational movements in three axes. Three translational movements

consist of medio-lateral movement, antero-posterior movement, and superior-inferior movement. The rotational movements are pelvic rotation, pelvic tilt, and pelvic rotation about medio-lateral axis. Details of pelvic motion were illustrated in Section 3.2.2.

The PA mechanism is designed to provide actuated assistance for **five** pelvic movements. Pelvis has six movements (details has been highlighted in Figure 3-6), however only three movements are significant movements during walking. The three movements are pelvic rotation, pelvic tilt, and translational medio-lateral movement.

The PA mechanism has a pair of robotic arms. Each robotic arm consists of a sub-mechanism and a lateral shift mechanism. The two robotic arms hold the subject at both sides of pelvis as shown in Figure 5-3. The subject is secured within the robotic arm with a special designed harness.

Figure 5-3: Configuration of robotic arms of pelvic assistance mechanism

Each robotic arm provides three actuated motions. With two robotic arms of the PA, the three translational movements and two rotational movements of the pelvis can be achieved. The pelvic rotation about the medio-lateral axis is made passive, with the range of motion restricted by the harness to $\pm 5^\circ$.

Sub-mechanism of PA comprises actuators 1 and 2 and provides the motion in the sagittal plane. Actuator 3 is connected to the end effector of the sub-mechanism

provides the lateral shifting motion as shown in Figure 5-4. The position of the end effector is indicated by balloon 1. The sagittal plane's motion (x_{g3} , z_{g3}) of pelvis is provided by the linear motion of s_{g1} and s_{g2} . The pelvic motion in the y -axis (lateral movement) is controlled by actuator 3 through a rack and pinion mechanism.

Figure 5-4: CAD illustration of PA mechanism a) isometric view, b) Movement of PA in the sagittal plane of the right side and c) Lateral shift mechanism of the right side

The kinematic chain of the sub-mechanism is depicted in Figure 5-5. Subscript g denotes left and right sides, in which $g = l$ for left side and $g = r$ for right side.

Figure 5-5: a) Kinematic representation of PA sub-mechanism and (b) effective and designed workspace, ($x = 0, z = 0$ at end effector)

Figure 5-6: Designed workspace for PA mechanism, with the end effector set as reference coordinates a) Motion in sagittal plane and b) Motion in frontal plane

5.2.2 Body Weight Shifting and Body Weight Support

During gait locomotion, human constantly shift the body weight from previous supporting leg to the next supporting leg, to facilitate the swinging of the previous supporting leg. Body weight shifting is part and parcel of the pelvic motion. The lateral movement of the pelvic shifts the Center of Mass (CoM) of the body to the supporting leg. The provision of the lateral movement by the proposed pelvic assistance mechanism provides body weight shifting.

5.2.3 Realization of Over Ground Mobility for Robotic Assisted Gait Rehabilitation

Mobile platform is the base of *NaTure-gaits*. The main function of the mobile platform is to provide the progression for the entire system and the subject during gait rehabilitation. Mobile platform also serves as the carrier of the robotic orthosis, pelvis assistance mechanism, controller, power source, and any other electronics components of *NaTure-gaits*. Two motorized wheels are mounted at the rear of mobile platform. Each wheel is independently controlled, and it is possible for the mobile platform to follow straight or curved path. Thus the gait rehabilitation is not limited to progression in a straight line only. Figure 5-2 shows the actual build of mobile platform.

The speed of the mobile platform was designed and customized based on several considerations, such as comfortable normal walking speed of a healthy person and patient. The average of natural walking speed for a healthy adult is 1.5 m/s (Aged 20 – 65 years) [110]. Our gait study of 70 healthy subjects of sampled population (Aged 22 – 51 years) shows average natural walking speed of 1.22 m/s, and slowest natural walking speed of 0.55 m/s is observed.

5.2.4 Reciprocal Lower Limb Stepping with Robotic Orthosis (RO)

Robotic orthosis is the module in *NaTure-gaits* providing actuated assistance to complete the gait locomotion of the lower limb. Six primary degrees of freedom (DoFs) are found on human leg, three at the hip, one at the knee, and two at the ankle. The determination of the DoFs required for an orthosis depends on the task requirement. For this study, after literature review and discussion with clinical practitioners, the robotic orthosis is designed to provide actuated assistance in the sagittal plane, for hip, knee, and ankle joints.

Figure 5-7: Design and features of robotic orthosis for *NaTure-gaits*

Table 5.2: The designed range of motion (ROM) for Robotic Orthosis
(Presented with permissible ROM of human and ROM of human during walking)

		<i>Range of Motion (Sagittal plane)</i>		
		<i>Permissible</i> [150]	<i>Walking</i> [29]	<i>Designed</i>
Hip	Flexion	122°	20°	50°
	Extension[#]	10°	11°	15°
Knee	Flexion	134°	60°	80°
	Hyperextension	0°	0°	0°
Ankle	Dorsiflexion	13°	9°	10°
	Plantarflexion	56°	18°	20°

[#] The permissible range of hip extension is 10° as recorded in reference [150]. As recorded in reference [81], the permissible range has a range of 10° to 30°. The discrepancies of the value could be due to measuring method. The designed ROM for hip extension is 15°.

The robotic orthosis has a total of six degrees of freedom, three on the right side and three on the left side. It is designed as a pair of anthropomorphic legs, which mimic the shape of human leg skeleton. The length of the robotic orthosis for the thigh and shank can be adjusted to fit different subjects. The design of the robotic orthosis is shown in Figure 5-7. The range of motion (ROM) designed for each joint is

provided in Table 5.2 The ROM is limited by hardware limiter. The mechanism joints will not travel beyond the designed ROM to ensure the safety of the user.

5.2.5 Control Modules

Three mentioned modules of *NaTUre-gaits* are controlled by a control module using PXI system from National Instrument. PXI is a rugged PC-based platform for measurement and automation systems. A PXI system consists of four main components: rugged chassis, system controller, peripheral modules, and software. Overall hardware construction of PXI system is shown as follows:

Figure 5-8: Components of PXI system

PXI chassis: The chassis provides the rugged and modular packaging for the system. Chassis generally are available in 4-, 6-, 8, 14-, and 18-slot. The chassis combines industry-standard PC components, such as PCI bus, with advanced triggering and synchronization extensions on the high-performance PXI backplane. The chassis used in control module is NI PXIe-1062Q which provides 1 PXIe system slot for controller, 1 PXIe peripheral slot, 2 Hybrid slots and 4 PXI slots.

PXI controllers: NI PXIe-8115 was used in control module. With embedded controllers, there's no need for external PC. Embedded controllers include standard features such as an integrated CPU, hard drive, memory, Ethernet, video, serial, USB and other peripherals. NI PXIe-8115 is compatible with both Windows OS and LabVIEW Real-Time.

Peripheral modules: National Instruments offers more than 500 different modules, and, because PXI is an open industry standard, more than 1500 modules are available from more than 70 vendors. Three types of peripheral modules were used in *NaTure-gaits* application: motion control, signal conditioning and multifunction data acquisition. Two motion controller cards NI PXI-7358 were used. This motion controller offers 8 axes for stepper/servo motor. Data acquisition is integrated with signal conditioning on a single PXI card to achieve the best accuracy and throughput for strain gages, bridge-based transducers. NI PXIe-4330 was used to measure force from strain gages which is bridge-based sensors. A wireless data acquisition NI WLS-9163 with C series module NI 9205 were used to measure signal from flexi-force sensors and wirelessly transmit to the main controller.

Software: NI LabVIEW and Matlab were used as programming environments in *NaTure-gaits* system.

Figure 5-9: Control module of *NaTure-gaits*

5.3 Conclusions

A newly proposed robotic gait rehabilitation system, *NaTure-gaits*, has been presented. Essential features of robotic assisted gait rehabilitation, such as unrestricted

pelvic motion assistance, lower limb motion assistance, body weight support, and over ground walking experience are made possible with *NaTure-gaits*.

Three robotic modules are designed in this work to enable the robotic gait rehabilitation system to provide body weight supported gait rehabilitation, with assistance provided to hip and lower limb movement, in the context of over-ground walking. The unique feature found on *NaTure-gaits* is the provision of pelvic motion assistance and body weight support with the pelvic assistance mechanism.

Pelvic assistance mechanism is developed for pelvic motion assistance and body weight support. The mechanism is a two-five DoFs robotic arms provide the essential movements for the pelvis. Without the restriction of cable harness body weight support, natural pelvic motion can be induced by pelvic assistance mechanism and also promoting body weight shifting. A six DoFs robotic orthosis is developed for the lower limb motion assistance. It has the similar features of lower limb orthosis found on most robotic gait rehabilitation system. The lower limb joints' (hip, knee, and ankle) movement in the sagittal plane is assisted by the robotic orthosis.

Chapter 6

***SUBJECT-COOPERATIVE*CONTROL STRATEGY FOR ROBOTIC ASSISTED GAIT REHABILITATION**

Originally, robotic rehabilitation devices only moved the patient along predefined trajectories and did not adapt their movements to the activity of the patient. This position controlled training also known as passive training is well suited for patients who are in the early phase of rehabilitation or severely affected. However, passive training strategy does not provide an ideal training for patients who have capability of some voluntary motor control. If patients are trained with totally passive training strategy, they tend to train with reduced activity of muscles and metabolism. For example, people with SCI who walk in a robotic gait training device with position control consumed 60% less energy than in traditional therapist assisted therapy [30]. Moreover, if patients try to walk actively while the robotic rehabilitation device remains passively support, they will work against the resistance of the device, which result in abnormal muscle activity patterns [31]. To overcome these shortcomings, *subject-cooperative* control strategies are being developed by numerous research groups. These control strategies allow patients to influence robot's movements and to increase their effort during the training process while still providing sufficient guidance and support to ensure a complete walking pattern.

To allow the patient's voluntary participation in the gait training process, some approach such as gait adaptation, adaptive impedance control, virtual model control and path control were introduced. Details of the control strategy and state of the art of *subject-cooperative* control was introduced in Section 2.5. In this Chapter, the gait pattern adaptation control strategy is introduced. Human-machine interaction force is estimated to measure the degree of activity of the human subject walking with the system. Walking speed will be updated based on the degree of voluntary participation, resulting in adjustment of walking gait pattern.

6.1 Locomotion Control Strategy based on a Gait Pattern Generation Model

Overview of locomotion control strategy based on gait pattern generation model is illustrated in Figure 6-1. The first step is to obtain the basic information and measure the anthropometry parameters of the subjects. Age, gender, height, and weight were included in basic information and ASIS breadth, thigh length, shank length and foot length composed anthropometric parameters.

Basic information of subjects was used as input of Gait Parameter Prediction Model. The input of walking speed could be determined by the therapist or selected from the suggested range of walking speed from the model. When walking speed was selected for a subject, Gait Parameter Prediction Model would provide corresponding stride length and cadence.

Gait parameters and anthropometric data of selected subjects were used as input for Gait Pattern Prediction Model to plan reference gait pattern for each individual (details in Chapter 3). Subsequently, a minor modification for predicted gait patterns was carried out to improve the foot contact and coordination between PA and RO before input to *NaTure-gaits*. This process was completed by Task Specific Model and details of this model were introduced in Chapter 3.

Invert kinematic of Pevic Assistance (PA) mechanism was used to convert pelvic angle waveforms to encoder counts for PA motors. A simple PID controller was applied for PA position control. Similar approach was used for Robotic Orthosis (RO) mechanism. For Mobile Platform (MP), speed control was used so that the two wheels of MP mechanism moving at the desired walking speed in progression direction.

Figure 6-1. The locomotion control strategy based on gait pattern generation model

6.2 Gait Pattern Adaptation Control Strategies

Gait speed is a valid and reliable measure of recovery after stroke and a valuable indicator of future health and mobility[151]. Results shows that the swing phase duration, single stance duration and double phase stance duration are significantly affected by the gait speed. Variability of cadence and stride length largely decreases as walking speed increase. Joint trajectories of knee and ankle joint, as well as leg muscle EMG activity patterns change largely at slow walking speed which might slow

down the recovery rate of patients[152]. The improvement of the post stroke patients is determined by their improvement in gait speed. Increasing gait speed can be a meaningful improvement in disability level [153] and it decreased the time of swing and time of support which suggests an improve in stability[154]. Continuous walking at maximum walking speed can also increase walking endurance [155].

Figure 6-2 shows the gait pattern adaptation control strategy implemented in *NaTure-gaits*. The proposed control strategy contains two modules which are high-level controller and low-level controller. In the high level controller, human-machine interaction force f was first measured using strain gauge sensors. The values obtained from strain gauge reflected the degree of activity of the human subject walking in the robotic system. The level of a subject's activity varies from totally passive to active participation and it was represented as an index in the range of $[0, 1]$. Based on the activity index, a suitable walking speed v^d was selected within a range of $[0.55, 1.3]$ m/s. The range of walking speeds was calculated from 700 walks of 70 healthy subjects in motion capture experiment. When walking speed was determined, gait parameters were estimated and the gait pattern adaptation model was applied to generate gait patterns.

In the low-level controller, the gait patterns were played at a slower cadence on *NaTure-gaits* because walking speed of subjects with severe gait deficit is less than 0.4 m/s [156]. A well-known PD controller was used in low-level controller to control DC motors to follow desired gait pattern generated from high level controller. In Figure 6-2 v^d and v_{MP} are desired walking speed and linear velocity of the system in progression line; θ_i^d and θ_i are desired and actual angular trajectories, respectively. e_i is error input to low-level controller. D/A and A/D are digital to analog converter and vice versa. PA, RO and MP are Pelvic Assistance, Robotic Orthosis and Mobile Platform module of *NaTure-gaits* system, respectively.

Figure 6-2: The gait pattern adaptation control strategy

6.2.1 Measurement of Human-machine Interaction Force

When walking with robotic orthosis (RO), each thigh of the subject is supported by force F in the moving direction. Figure 6.3 shows an iSCI subject walking with *NaTure-gaits* and the human-machine interaction at thigh segment. The information of human-machine interaction forces can be extracted from the bending strain of the RO's thigh segment.

Figure 6-3: Human-machine interaction forces under the position control mode

Bending strain of the cantilever beam aforementioned was measured by strain-gauge sensors placed on top and bottom of the thigh segment of RO. The connection of these sensors is based on the concept of a Wheatstone bridge. Figure 6-4 show a general resistive Wheatstone bridge circuit diagram. The Wheatstone bridge is the electrical equivalent of two parallel voltage divider circuits. (R_1, R_2) compose one voltage divider circuit and (R_3, R_4) compose the second one. The output of a Wheatstone bridge is V_{CH} which is the voltage between the middle nodes of the two voltage dividers. When there's a change in strain applied to the beam, the resistance of the sensing elements in the Wheatstone bridge will be changed, resulting in a bridge output voltage that is proportional to the change in strain. The output voltage of the bridge scales with the excitation voltage V_{EX}

Figure 6-4: The basic Wheatstone bridge circuit diagram

Common configuration types of strain gauge include quarter-bridge, half-bridge and full-bridge corresponding to the number of active sensing elements in Wheatstone bridge circuit is one, two or four sensors. In this work, strain-gauge sensors on thigh segment of RO were configured in full-bridge type to measure bending and reject the axial. The placement and configuration of train gauge sensors are shown as follows:

Figure 6-5: The strain-gauge and full-bridge configuration

The full-bridge configuration of these strain gauge sensors has the following characteristics:

- Four active strain-gauge elements. Two are mounted in the direction of bending strain with one on top of the thigh segment and the other on the opposite side. The other two act together as a Poisson gauge and are mounted perpendicular to the principle axis of strain with on top and the other on the bottom.
- Rejects axial strain

- Sensitivity $\sim 1.3\mu V/V$ per $\mu\epsilon$, for Gauge Factor ($GF=2$)

The NI PXIe-4330 was used to obtain the output voltage of the bridge in scale with the excitation voltage. This module provides eight simultaneously sampled input channels for interfacing to strain-gauge bridges. The circuit wiring diagram for the full-bridge configuration and NI PXIe-4330 are shown as follows:

Figure 6-6: The full-bridge circuit diagram

The following symbols apply to the circuit diagram and equations:

R_1, R_2 : Active element measuring compressive and tensile Poisson effect ($-v\epsilon$ and $+v\epsilon$, respectively)

R_3, R_4 : Active element measuring compressive strain and tensile strain ($-\epsilon$ and $+\epsilon$, respectively)

R_S : Shunt calibration resistor located inside the NI PXIe-4330

R_L : Lead resistance

GF : Gauge Factor, specified by the manufacturer. In this work, the strain gauges were from Tokyo Sokki Kenkyujo Co and $GF=2.1$

ν : Poisson's ratio. $\nu = 0.334$ for aluminum

V_{CH} : Measured voltage of the bridge

V_{EX} : Excitation voltage provided by the NI PXIe- 4330

V_r : Offset compensation ratio metric bridge output which is done internally on the NI PXIe-4330 and it is defined by

$$V_r = \frac{V_{CH}^{(train)} - V_{CH}^{(unstrained)}}{V_{EX}} \quad (6.1)$$

The module reading can be converted to the strain feedback as follows:

$$\varepsilon = \frac{-2V_r}{GF(1+\nu)} \quad (6.2)$$

6.2.2 Interaction-force Profile References and Interaction Index

For the purpose of calculating the reference of interaction-force profiles, the *NaTure-gaits* system was run in two different modes. During the first mode, the system was run without any subject attached. There was no interaction-force in this mode, the force profile measured in this situation was from gravity and acceleration of the RO's thigh segment. For the second mode, the subjects was asked to walk with the sytem and allow it to guide the trajectory of their legs in position control mode. The seconde mode is passive walk and subjects were asked not to contribute any movement during this mode. Lower limb kinematic data and strain gauge values were recored for 10 walking gait cycles (GCs) during each mode. By averaging the human-machine interaction forces for 10 GCs, a reference force profile representing no-subject walking and passive walking was calculated. The results are shown in Figure 6-7.

Figure 6-7: Reference of interaction-force profiles

When the reference of interaction force profiles were available, the interaction index would be calculated as follows:

$$f_i = \begin{cases} f_i^{passive}, & \text{when } |f_i| > |f_i^{passive}| \\ f_i^0, & \text{when } |f_i| < |f_i^0| \\ f_i, & \text{otherwise} \end{cases} \quad (6.3)$$

$$r_{active} = \frac{1}{N} \sum_{i=1}^N \left| \frac{f_i - f_i^{passive}}{f_i^0 - f_i^{passive}} \right|$$

where f_i^0 and $f_i^{passive}$ is the interaction force profile of no-subject walking, passive walking, respectively; f_i is the measured force; $i=1..N$ is one instance in one GC; r_{active} is the interaction index and its value in the range of [0,1].

6.2.3 Design of Low-level Controllers

Plant of DC motor has the form:

$$G_m = \frac{K_m}{T_m s^2 + s}$$

where $K_m = 69.5$ and $T_m = 0.33$. These values from lower limb DC motors and they were obtained from experiments.

The PID controller was applied as low level controller and it has the form

$$G_c = K_p + \frac{K_i}{s} + K_d s$$

The close loop system is expressed as follows:

$$G = \frac{G_m G_c}{1 + G_m G_c}$$

Analysis of the characteristic function using Routh-Hurwitz criteria can be applied to show the stability of close-loop system as follows:

$$1 + G_m G_c = 0$$

$$\Leftrightarrow s^3 + \left(\frac{1 + K_d K_m}{T_m}\right)s^2 + \frac{K_p K_m}{T_m}s + \frac{K_i K_m}{T_m} = 0$$

Denote the coefficients of characteristic polynomial function as the following definitions:

$$a_1 = \frac{1 + K_d K_m}{T_m}; a_2 = \frac{K_p K_m}{T_m}; a_3 = \frac{K_i K_m}{T_m}$$

For the third order polynomial function, the Routh-Hurwitz criteria for stability is:

$$a_1 > 0; a_3 > 0; a_1 a_2 > a_3$$

The proportional gain and derivative gain values K_p and K_d were adjusted to keep the angles tracking with minimal overshoot while maintaining stability throughout the step and reaching the target angle within the allowable error quickly enough to track the trajectory during walking. The integral gain K_i which aids in eliminating steady state errors due to gravity and other factors was not used in *NaTure-gaits*. Because many subjects with paraplegic gait also have muscle spasticity, their muscles will against of the system's movement forcing the integral errors term to wind up. Using integral gain would result in overpowering the spasticity to move the joint and could seriously injure the subject. To eliminate this risk, the integral term was not used.

6.3 Assessment of the Gait Pattern Adaptation Control Strategy with *NaTure-gaits*

6.3.1 Experimental Setup

The objectives of this experiment were to evaluate if the gait pattern adaptation control strategy can produce appropriate walking gait pattern for different walking speed and if the voluntary participation from the human subject could be increased. Lower limb angle trajectories were recorded during the walking experiment. Data for assessment of effort from the subjects included strain gauge signal, body weight support level and control signal to the DC motors.

Three healthy subjects with no history of neurologic disorders gave written informed consent and participate in the study. The subjects were instructed to walk with the *NaTure-gaits* with two different scenarios: walking at constant speed using position control and walking with varied walking speed using gait pattern adaptation control. The walking trial is 10-meter walk and it was repeated three times for each scenario.

6.3.2 Results and Discussions

6.3.2.1 Gait Pattern Adaptation for Different Walking Speeds

The waveforms angles of hip and knee joint when a subject walked at a constant speed with *NaTure-gaits* are shown in Figure 6-8. Seven gait cycles were performed during 100 seconds. The result shows that the proposed control algorithm can provide a consistent walking gait pattern to the system when it's controlled by position control mode to walk at constant speed.

Figure 6-8. Lower limb waveforms when walking at constant speed

The results of gait pattern adaptation control strategy when subjects tried to make effort and increase his walking speed are shown in Figure 6-9 and Table 6.1. During the experiment, the walking speed was changed from slow speed to normal speed (11 cm/s to 24.7 cm/s). The range of walking speed was determined from motion capture experiment of normal walking from healthy subjects. Walking speed is totally defined by spatio-temporal parameters of gait (stride length and cadence). Results from Figure 6-9 shows that gait pattern adaptation control model are able to update both spatio- and temporal- parameter when walking speed is changed. For example, at slow walking speed (11 cm/s), the stride length and cadence given by the gait pattern adaptation model were 103.9 cm and 94.8 seconds, respectively. When walking speed was increased to 24.7 cm/s, stride length and cadence were 141.5 cm and 57.3 seconds, respectively. Figure 6-9 also shows that the peaks of hip joint angles and knee joint angle waveforms were increased when walking speed increased. The results from gait pattern adaptation control model agreed with the study of human locomotion using motion capture experiments.

Figure 6-9: Hip and knee angle waveforms in sagittal plane when walking at different speed using speed adaption control mode

Table 6.1: Adaptation of gait parameters based on walking speed using gait pattern adaptation control algorithm

Walking speed (cm/s)	Stride length (cm)	Gait Cycle (s)	Hip (degrees)		Knee (degrees)	
			Peak_a	Peak_b	Peak_a	Peak_b
11	103.9	94.8	21.5	-14.1	47.9	6.7
13.25	108.5	81.8	21.9	-14.9	47.9	7.2
15.54	112.2	72.2	22.4	-14.9	48.0	7.5
17.8	119.1	66.8	22.4	-15.2	48.3	8.1
22.4	134.7	60.1	23.5	-16.4	48.6	9.6
24.7	141.5	57.3				

Figure 6-10 shows two snapshots from the walking experiment with *NATUre-gaits* system. Step length of the subject before he increased his walking speed is labeled as SL_a and step length after the walking speed was increased is labeled as SL_b . The figure reveals a noticeable increment of step length when the subject tried to walk faster with the *NATUre-gaits* system.

Figure 6-10: Step length at different gait speeds

6.3.2.2 Evaluation of Degree of Voluntary Participation from Subjects

Degree of voluntary participation from the subjects in this work was assessed by using parameters such as level of body weight support, level of human machine interaction level and current generated by the driver to run DC motor. Those parameters are represented by values of strain gauge at the arm of Pelvic Assistant (PA) mechanism, values of strain gauge at thigh segment of the Robotic Orthosis (RO) and control signal to the DC motor at hip joint. The results are respectively shown in Figure 6-11 to Figure 6-13. The plotting results are the average of 10 walking gait cycle of all participants. Results show that the level of body weight support and interaction force when the gait pattern adaptation control was turned off are bigger compare to the interaction force when the gait pattern adaptation control was used (Figure 6-11 and Figure 6-12). In the first scenario, the system was controlled in position control mode and it induced a fixed gait pattern on the subjects

and they walked at a constant speed. The voluntary effort of subjects was ignored under the position control mode. On the other hand, gait pattern adaptation control algorithm allows the subjects to be involved when the level of voluntary participation increased. This control algorithm modified the walking gait pattern of *NaTure-gaits* and increase walking speed to follow the subject during walking experiment. Since the subjects were allowed to support themselves, the level of body weight support from the robotic system was reduced. Similarly, when the gait pattern adaptation control algorithm was applied, the robotic orthosis followed the movements of the subjects lower limb instead of constrained these movements. Therefore, the interaction between the robotic system and the subjects was decreased as expected. Figure 6-13 illustrates a decrement of control signals to DC motor at hip joint when the proposed control algorithm was applied. When the subjects were allowed to exert their power to bear more on their body weight and reduce the interaction force with the system, the power generated by the motors was reduced.

Figure 6-11: Relationship between strain gauge value and the level of body weight support

Figure 6-12: Relationship between strain gauge value and the level of human machine interaction at thigh segment

Figure 6-13: Control signals to DC motor at the hip joint

6.4 Practical Implementation of the Gait Pattern Adaptation Control Strategy on *NaTure-gaits*

Ground reaction force (GRF) and center of pressure (CoP) are commonly used in gait analysis, and often taken into account when evaluating the effectiveness of a robotic gait assisted device. This work aims to 1) investigate the impact on vertical

ground reaction force (vGRF) and CoP path when training with a robotic gait rehabilitation system, *NaTure-gaits* and 2) verify the effectiveness of gait pattern adaptation control strategy. A wearable force system was developed to measure vGRF and CoP path could be computed from the measured vGRF data. Five healthy subjects were instructed to finish 10-meter walks under three scenarios: pre-training, during training with *NaTure-gaits*, and post-training. vGRF data and CoP paths were measured and analyzed.

6.4.1 Experimental Setup

Five healthy male subjects were recruited from the general student population at the Nanyang Technological University (NTU), Singapore. These subjects have neither neurological injury nor gait disorder. The subjects were instructed to perform 10-meter walk under three conditions: normal walking, during training with *NaTure-gaits* and post-training. Vertical Ground Reaction Force (vGRF) was collected during the experiments. Two types of gait patterns were used on *NaTure-gaits* for comparison: gait pattern generated by Gait Pattern Generation Model and the other one was obtained from Clinical Gait Analysis (CGA). Each subject walked four times and they were not informed which type of gait pattern they were going to experience. The effectiveness of the Gait Pattern Generation Model was assessed by using the feeling feedback from the subjects and by the analysis of CoP paths. The experiment set up is shown in Figure 6-14.

Figure 6-14: GRF data collection experiments (a) walking without *NaTure-gaits* before and after training, (b) during training with *NaTure-gaits*

6.4.2 Implementation of the Gait Pattern Generation Model

The first step is to obtain the basic information and measure the anthropometry parameters of the subjects. Age, gender, height, and weight were included in basic information and ASIS breadth, thigh length, shank length and foot length composed anthropometric parameters. Subjects data are summarized in Table 6.2, S1-S5 indicates subject number one to subject number five.

Table 6.2: Basic information and anthropometry parameters of the trial subjects

	Age	Gender	Height (cm)	Weight (kg)	ASIS Breadth (mm)	Thigh Length (mm)	Shank Length (mm)	Foot Length (mm)
S1	24	Male	173	68	238	460	420	250
S2	33	Male	168	61	254	405	403	243
S3	24	Male	175	62	272	500	430	251
S4	22	Male	173	66	238	445	450	266
S5	23	Male	160	70	233	332	391	223

Basic information of subjects was used as input of Gait Parameter Prediction Model (Figure 6-1). The input of walking speed could be determined by the therapist or selected from the suggested range of walking speed from the model. When walking speed was selected for a subject, Gait Parameter Prediction Model would provide corresponding stride length and cadence. The predicted and selected basic gait parameters are listed as follows:

Table 6.3: Selected basic gait parameters for the trial subjects based on the predicted values

	Predicted Walking Speed (cm/s)	Selected Walking Speed (cm/s)	Predicted Stride Length (cm)
S1	116.60 $\pm$ 4.43	113.07	126.67
S2	119.28 $\pm$ 4.53	114.58	130.27
S3	115.91 $\pm$ 4.50	113.01	123.35
S4	114.69 $\pm$ 4.36	97.76	123.29
S5	113.25 $\pm$ 4.30	115.45	116.28

Gait parameters and anthropometric data of selected subjects were used as input for Gait Pattern Prediction Model to plan reference gait pattern for each individual (Figure 6-1). Details of Gait Pattern Prediction Model were introduced in Chapter 3.

Subsequently, a minor modification for predicted gait patterns was carried out to improve the foot contact and coordination between PA and RO before input to *NaTure-gaits*.

6.4.3 Measurement of Vertical Ground Reaction Force (vGRF) and Center of Pressure Paths (CoP)

Five flexi-force sensors (by Tekscan, Inc) were placed under each foot to measure the ground reaction force. The location of the sensors on the subject's feet is shown in Table 6.4as follows:

Table 6.4: Annotations and anatomical positions of force sensors

Number		Anatomical Position
Right Foot	Left Foot	
S1	S6	Hallux (Big toe)
S2	S7	1st Metatarsal
S3	S8	3rd Metatarsal
S4	S9	5th Metatarsal
S5	S10	Heel

The force data can be collected by connecting these sensors to an Op-Amp circuit and a wireless data acquisition device (NI wireless DAQ, model no: NI-WLS 9163). The setup of DAQ system, as shown in Figure 6-15, allow the NI controller to collect data remotely during the experiment.

Figure 6-15: Wireless setup of the DAQ system

Using the right heel strike at the first step (step 1) and the line of progression, the global coordinate system (OXY) can be defined. Figure 6-16 shows the global coordinate OXY and the footprint after walking n steps, oxy is the local coordinate, SL and SW are stride length and stride width, respectively.

Figure 6-16: Definition of global coordinate and sensor position

Assuming that SL and SW are constant during the walking process, the location of force sensors in global coordinate system after n walking steps can be calculated as follows:

$$\begin{bmatrix} \mathbf{X}_{i,n} \\ \mathbf{Y}_{i,n} \end{bmatrix} = \begin{bmatrix} -1^j \frac{SW}{2} \\ (n-1) \frac{SL}{2} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_i \\ \mathbf{y}_i \end{bmatrix} \quad (6.4)$$

where i is the sensor index $i=1$ to 10 ; j is the foot index, $j=1$ for left foot and $j=2$ for right foot; $(\mathbf{x}_i, \mathbf{y}_i)$ is position of sensor i in local coordinate.

Therefore, the location of instantaneous CoP positions in global coordinate system ($\mathbf{X}_{COP}, \mathbf{Y}_{COP}$) is given by:

$$\begin{aligned}
\mathbf{X}_{COP} &= \frac{\sum_{i=1}^5 \left(\mathbf{x}_i + \frac{SW}{2} \right) F_i + \sum_{i=6}^{10} \left(\mathbf{x}_i - \frac{SW}{2} \right) F_i}{\sum_{i=1}^{10} F_i} \\
\mathbf{Y}_{COP} &= \frac{\sum_{i=1}^5 \left(\mathbf{y}_i + \frac{(n-1)SL}{2} \right) F_i + \sum_{i=6}^{10} \left(\mathbf{y}_i + \frac{(n-1)SL}{2} \right) F_i}{\sum_{i=1}^{10} F_i}
\end{aligned} \tag{6.5}$$

where F_i is the instantaneous vertical ground reaction force at sensor i .

6.4.4 Results

6.4.4.1 Impact of NaTure-gaits on Vertical Ground Reaction Force

The results of vGRF for both right and left leg in one gait cycle were calculated for two conditions: self-paced normal walking speed and walking with *NaTure-gaits*. The results are illustrated in Figure 6-17.

Figure 6-17: Vertical ground reaction force (solid line: normal walking dotted line: walking with *NaTure-gaits*)

It was found that vGRF of normal walking increase in weight acceptance, decrease through mid-stance and increase again to the second peak at push-off. The result is agreed with previous studies [110, 144-146]. The results confirm that the use of flexi-force sensors for vGRF acquisition is feasible for evaluating pattern of vGRF as bio-feedback from subject. It appears that the vGRF when walking with *NaTure-gaits* is smaller compared to normal walking because part of the subject's body weight was supported by pelvic assistance (PA) mechanism of the robotic system. The second peak which contributes to push-off during walking was missing. A more

natural foot-ground contact is desired and improvement of the proposed model as well as mechanism design of the foot can be considered in future direction to overcome this limitation.

6.4.4.2 Impact of NaTure-gaits training on CoP Paths

After GRF data was collected, the CoP paths for pre-training, during training with *NaTure-gaits* and post-training were compared. Figure 6-18 shows that the general shift of CoP is similar for normal walking and assisted walking with the system. However, the shift of CoP is not smooth. This implied that the subject was in a state of imbalance. There may be because the motion of *NaTure-gaits* was not totally smooth. For example, the MP did not produce a smooth linear motion and the backward-forward swinging momentum caused the imbalance of the subject.

Figure 6-18: Comparison of CoP pattern and highlighted difference of a sample right step during right single stance before, during, and after training

Before training, the subject had a relatively longer foot flat period as it is observed that the CoP concentrated in the central area of the foot. However, during training, the subject had shortened the foot flat period and increased his contact on 3rd and 5th metatarsal. We hypothesized that the changing on foot contact during training

with the system was caused by the gait pattern induced by the robotic system. The use of gait pattern in the robotic system may not provide desired foot contact due to inherent errors (e.g. marker placement error, soft-tissue error) caused by the motion capture system.

On the whole, these results were consistent throughout most of the trials that the subject had during the *NaTure-gaits* training. The training with *NaTure-gaits* was able to provide the subject with close-to-original gait pattern as observed with similar CoP path produced before and during training. This was a positive feedback on the effectiveness of over ground walking training with *NaTure-gaits*.

Although the training only lasted for 10 minutes, the change in CoP pattern was noticeable during the unassisted walk after the training (Figure 6-18). This change of CoP pattern was prominent. Therefore, it can be concluded that the training was effective at impressing a gait pattern onto the subject.

6.4.4.3 Effectiveness of Gait Pattern Generation Model on *NaTure-gaits*: Feeling of Ground Contact

At the end of each walk, the subject is asked to rate the gait pattern induced, using 1 to 5 scale. 1 for not resemble his normal walking, and 5 for resemble his normal walking. The survey outcome is given in Figure 6-19.

Figure 6-19: Rating of two patterns by the subjects based on their trial experience

Three subjects have rated *GaitGen* pattern is better than CGA, one subject gave the same rating for the two patterns, and one subject rate the CGA 1 point higher than

GaitGen. Snapshots of the trial are given in Figure 6-20, showing how the subject walks with the *NaTure-gaits*.

Figure 6-20: Snapshots of video taken during the trial

6.4.4.4 Effectiveness of Gait Pattern Generation Model on *NaTure-gaits*: Body Weight Shifting

The CoP path was computed for the three subjects for normal walking and assisted walk with *NaTure-gaits* using two types of gait pattern: one was predicted by Gait Pattern Generation Model and the other one was obtained from CGA. The CoP paths of the subjects are plotted in Figure 6-21.

Figure 6-21: CoP path computed for the three subjects for different walks

6.4.5 Discussions

Figure 6-17 and Figure 6-18 reveal that vGRF and CoP paths during training are significantly affected due to the intervention of the robotic system. Analysis of CoP path after training reveals that the training process was effective at impressing a gait pattern onto the subject even when the training period is less than 10 minutes. The "after" curve was different from the "before" curve for healthy subjects from this figure due to motor "adaptation". The term motor "adaptation" has previously used to refer to distinct human motor behaviour [157, 158]. It is the modification of a movement from trial-to-trial under three criteria. First, the movement is identified as a specific action (e.g. "walking", "reaching") but changes in term of external interactions. Second, the change occurs with repetition of the original movement and is gradual over minutes to hours. Third, once adapted, individuals show "after-effect" and must "de-adapt" the behaviour with practice in the same gradual, continuous manner back to the original state.

When subjects were walking with *NaTure-gaits* system, their walking gait patterns were constrained (e.g. pelvic motions). After walking with the system, the subjects showed "after-effect" and the original walking pattern could not be retrieved immediately after being released from the system. The difference in CoP path of healthy subjects reflected the motor "adaption" behaviours which has been discussed in previous studies.

In general, most subjects felt that *GaitGen* pattern is more resemble their walking pattern (Figure 6-19). This trial also shows that individual-specific gait pattern generation would allow *NaTure-gaits* to induce a gait pattern that provide better walking experience for the subject.

For normal walking, the smooth transition of CoP from weight bearing leg to the next weight bearing leg can be clearly identified. As for robotic assisted walk with gait pattern from Gait Pattern Generation Model, similar CoP paths as of the normal walking are observed. However, the CoP does not starts at the heel, but rather, the CoP trajectory starts near third metatarsal. During robotic assisted walk with gait pattern from CGA, the CoP trajectory was not continue from current weight bearing foot to the next weight bearing foot.

Chapter 7

CONCLUSIONS AND FUTURE WORKS

The work presented in this thesis focused on individual-specific gait pattern planning model (*GaitGen*) and gait pattern adaptation control strategy for robotic assisted body weight supported gait rehabilitation. *GaitGen* was developed to generate gait patterns tailored for each individual with a wide range of walking speed. The model helps to fulfil the limitations of current gait pattern planning using Clinical Gait Analysis (CGA) data. The limitation of the method using the CGA data is that it cannot accommodate inter-subject differences. In addition, CGA data is limited to only one walking speed as per the published data. In the first stage of *GaitGen*, gait parameters of any individual are predicted given his/her age, gender, body height and weight. In second stage, a database of 700 gait patterns was collected via motion capture experiments. Motion capture data was analyzed in both time and frequency domain and Fourier coefficient vectors were used to represent walking gait patterns. Subsequently, generalized regression neural networks (GRNNs) were applied as non-linear mapping functions to predict the Fourier coefficient vectors from given gait parameters and anthropometric data of the target subjects. Finally, inverse Fourier transform is applied to generate the gait patterns using the predicted Fourier coefficient vectors. The individual-specific gait prediction model has been applied and validated for both lower limb angle waveforms and pelvic angle waveforms.

Gait pattern adaptation control strategy for robotic assisted gait rehabilitation has been developed for training subjects who have capability of some voluntary motor control. The proposed control strategy overcomes some limitations of position controlled training or passive training strategy. If patients are trained with totally passive training strategy, they tend to train with reduced activity of muscles and metabolism. Moreover, if patients try to walk actively while the robotic rehabilitation device remains passively support, they will work against the resistance of the device, which result in abnormal muscle activity patterns. The gait pattern adaptation control strategy allows the subject to interact with the machine and increase their effort in the training session. Based on the human-machine interaction, the walking speed is updated and walking gait pattern is modified during the training process. To realize

the usefulness of the gait pattern adaptation control strategy, a control module using PXIe technology from National Instrument was developed for an existing over-ground gait trainer, *NaTure-gaits*. The robotic system provides lower limb gait locomotion assistance, pelvic motion assistance, body weight support, and actual over-ground walking experience. Human subject trials have been successfully carried out for subjects who have neither neurological injury nor gait disorder. The recruited subjects adapted and walked well with the *NaTure-gaits* over-ground gait training system throughout the entire trial period though they had not experienced with the system before.

7.1 Summary of Contributions

The major contributions of this work are summarized as follows:

7.1.1 An Individual-specific Gait Pattern Planning Model (*GaitGen*)

An individual-specific gait pattern planning model (*GaitGen*) was developed to generate gait patterns tailored for each individual with a wide range of walking speed. In the first stage of *GaitGen*, a basic gait parameter prediction model was developed to generate self-selected slow or normal walking speed and the corresponding gait parameters of any individual given his/her age, gender, body height and weight. This work can provide reference of individual-specific basic gait parameters for therapists and doctors to facilitate gait pattern planning during gait rehabilitation.

Based on gait parameters (stride length, cadence) and anthropometric data of any target subject, an individual-specific gait pattern prediction model which capable of generating walking gait patterns was developed. Motion capture experiments of human walking were carried out and gait data were represented by Fourier coefficient vectors. A database which consisted of gait parameters, anthropometric data and Fourier coefficient vectors was constructed. From the database, a non-linear mapping function was designed and implemented to predict the Fourier coefficient vectors from given gait parameters and anthropometric data of the target subjects. Finally, the model applies inverse Fourier transform to generate the gait patterns using the predicted Fourier coefficient vectors.

The individual-specific gait prediction model has been applied and validated for both lower limb angle waveforms and pelvic angle waveforms. The accuracy of

the model was assessed by using the correlation coefficient, *MAD* and *TAD*. These parameters showed that the present model was able to generate gait patterns closer to the actual patterns compared to the gait patterns selected from CGA. These findings support the hypothesis that the proposed model is able to generate a gait pattern better than the CGA approach in terms of resembling the actual gait pattern of the targeted subject. The individual-specific gait prediction model has also been implemented to generate walking gait pattern for an over-ground gait rehabilitation system, *NaTure-gaits*.

Different walking speeds used in the robotic gait rehabilitation systems may be required at different stages of the training process. For example, slow walking speeds are usually used for training at the beginning stage. As the condition is improved, faster walking speeds are applied to provide a better therapeutic outcome. Walking speed is one of the key factors that influence the walking gait pattern. Therefore, if different walking speeds are required for the training purpose, suitable gait patterns must be planned for the robotic systems. The present model is able to update gait patterns in both spatio- and temporal- space when walking speed is changed.

From the clinical aspect of gait rehabilitation, functional recovery is maximized when locomotor training follows three major principles: practice, specificity and effort. The first two principles emphasize that inducing correct joint kinematics to a patient in a repetitive manner results in better therapeutic outcomes and more practicing leads to improved motor learning. Therefore, it's important to plan correct motions for robotic trainers given that the patients will learn the gait pattern imposed to them during training process. It has been shown that variability in gait patterns are associated with differences in anatomical properties and walking

speeds. The present model is able to plan correct gait patterns in robotic gait rehabilitation by considering inter-subject difference and variability in walking speed. Thus, it can improve the therapeutic outcomes and help patients regain functional capacity.

7.1.2 Coordinating and Synchronization for the Natural gait-like Walking Pattern on Robotic Gait Rehabilitation Systems

Clinical Gait Analysis (CGA) data in the robotic systems may not provide a natural gait-like walking pattern due to the inherent errors (e.g. marker placement error, soft-tissue error) caused by the motion capture system and difference in anthropometric data of different subjects. This work introduced a method to adjust the gait pattern from motion capture data to 1) obtain a correct coordination between pelvic and lower limb movement and synchronization between pelvic center movement in the line of progression and progression velocity for over-ground gait trainers which consist of pelvic assistance and robotic orthosis, *NaTure-gaits*, and 2) improve the foot contact of automated gait trainers. The method works on translating and coordinating the gait pattern for gait locomotion playback on robotic gait rehabilitation system.

An optimization model for proper foot contact in robotic assisted gait rehabilitation systems was developed. Motion capture experiments of human walking were carried out to collect pelvic and lower limb kinematic data. Subsequently, foot contact represented by heel trajectory and foot-to-ground angle was calculated by using lower limb kinematics. An optimization model using the Generic Algorithm (GA) was applied to adjust the lower limb joints angles for a better foot contact. The proposed model was required to maintain the smoothness of heel trajectory, foot-to-ground angles and lower limb joints angles after the adjustment process. Initial trials with an over-ground gait trainer (i.e. *NaTure-gaits*) were conducted and vertical ground reaction force (vGRF) was collected to evaluate the effectiveness of the proposed model. The results showed that the proposed model would be able to provide a better foot contact and realistic walking for the target subject on robotic training devices.

7.1.3 The Gait Pattern Adaptation Control Strategy in Robotic Gait Rehabilitation

Gait speed is a valid and reliable measure of recovery after stroke and a valuable indicator of future health and mobility. The improvement of the post stroke patients is determined by their improvement in gait speed. Increasing gait speed can be a meaningful improvement in disability level and it decreased the time of swing and time of support which suggests an improvement in stability. Continuous walking at maximum walking speed can also increase walking endurance.

To allow the patient's voluntary participation in the gait training process and maximize their walking speed during the rehabilitation training process, the gait pattern adaptation control strategy was introduced. Human-machine interaction force is estimated to measure the degree of activity of the human subject walking with the system. Walking speed will be updated based on the degree of voluntary participation, resulting in adjustment of walking gait pattern.

Experiments with healthy subjects were performed to evaluate if the gait pattern adaptation control strategy can produce appropriate walking gait pattern for different walking speed and if the active participation of the human subject can be indicated by the data from force sensors. The results of gait pattern adaptation control strategy showed that walking speed was changed from slow speed to normal speed (50 cm/s to 162 cm/s) during the experiments. Gait pattern adaptation control model was able to update both spatio- and temporal- parameter when walking speed is changed.

Human subject trials have been successfully carried out for subjects who have neither neurological injury nor gait disorder. The recruited subjects adapted and walked well with the *NaTure-gaits* over-ground gait training system throughout the entire trial period though they had not experienced with the system before. The subject trials verified the ability of *NaTure-gaits* in the provision of gait locomotion, through the proposed control strategy.

Degree of voluntary participation from the subjects in this work was assessed by using parameters such as level of body weight support, level of human machine interaction level and current generated by the driver to run DC motor. The gait pattern adaptation control algorithm allows the subjects to be involved when the level of voluntary participation increased. This control algorithm modified the walking gait pattern of *NaTure-gaits* and increase walking speed to follow the subject during

walking experiment. Since the subjects were allowed to support themselves, the level of body weight support from the robotic system was reduced. Similarly, when the gait pattern adaptation control algorithm was applied, the robotic orthosis followed the movements of the subjects lower limb instead of constrained these movements. Therefore, the interaction between the robotic system and the subjects was decreased as expected

The subject feedbacks about the feeling of walking pattern, changing of walking speed and the bearing of body weight were positive. The subjects feel comfortable walking with the system, they can feel the robot actively changing its speed to adapt to their effort and they have a good feeling of over-ground walking by bearing their own weight. The significant reduction on the laborious demanding and time consuming are also demonstrated.

7.2 Future Works

7.2.1 Individual-specific Gait Pattern Planning Model (*GaitGen*)

An individual-specific gait pattern planning model (*GaitGen*) was developed to generate gait patterns tailored for each individual with a wide range of walking speed. In the first stage of *GaitGen*, a basic gait parameter prediction model was developed to generate self-selected slow or normal walking speed and the corresponding gait parameters of any individual given his/her age, gender, body height and weight. The gait parameter prediction model introduced in Chapter 3 has adopted Generalized Regression Neural Network (GRNN) as a non-linear mapping function between input vectors and output of gait parameters. The GRNN has good accuracy in predicting the basic gait parameters. However, using support vector regression method may improve the accuracy of the predicted outputs. Support vector regression (SVR) and support vector classification (SVC) are the two types of support vector machine (SVM) which introduced in year 1995. SVM has become one of the preeminent machine learning paradigms and it has been recognized as one of the ten best algorithms in data mining [159].

The objective of the second stage of *GaitGen* is to develop an individual-specific gait pattern prediction model that is able to generate walking gait patterns based on gait parameters (stride length, cadence) and anthropometric data of any target subject. In this work, the human walking gait pattern is defined by three rotational movements

of pelvis and lower limb joint angles in sagittal plane in one gait cycle. The second stage of *GaitGen* can be extended for the three linear movements of pelvis during human walking. The author also suggests implementing the gait pattern prediction model for lower limb joint angle waveforms in three-dimensional space.

7.2.2 Foot Trajectory in both Stance Phase and Swing Phase

Chapter 4 of this research work introduced an optimization model to adjust the gait pattern from motion capture data to improve the foot contact in over-ground robotic gait rehabilitation. This method controls the foot trajectory during stance phase or period from heel strike to toe off. A method provides proper foot clearance in swing phase may be worth considering and combining with the proposed method which improve the foot contact. It may be an option to use functional electro stimulation (FES) in combination with the *NaTure-gaits* at a certain phase of locomotion training. With FES, a more or less natural push-off as well as foot clearance during swing can be generated.

7.2.3 EMG-based Control for Robotic Gait Rehabilitation

Electromyography (EMG) is becoming more and more a standard tool in the study of human movement. EMG may be considered to be used to control the robotic system according to the subjects' intention since EMG directly reflects the subjects' muscle activity level in real time. EMG data can be used to measure the level of voluntary participation from the subject. When an increment of voluntary participation from the subjects is detected via EMG signals, a robotic system may be controlled to increase its walking speed and follow the subjects. EMG-based control could be a better biofeedback compare to strain gauge since EMG data directly reflects the subjects' muscle activity level. It's suggested to work with the proposed gait pattern adaptation control strategy as a biofeedback module in future work.

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Appendix-A

Experimental Data of Gait Parameters for the Fifty Subjects

Subject	Walk	Age	Gender	Speed State	Height (cm)	Weight (kg)	Walking Speed (cm)	Stride (cm)	Cadence (steps/min)
1	1	48	Female	Slow	158	50	83.60	98.94	101.40
1	2	48	Female	Slow	158	50	101.74	108.14	112.90
1	3	48	Female	Slow	158	50	93.21	101.32	110.40
1	4	48	Female	Normal	158	50	114.53	114.06	120.50
1	5	48	Female	Normal	158	50	119.56	116.17	123.50
1	6	48	Female	Normal	158	50	121.92	118.47	123.50
2	1	22	Female	Normal	155	59	108.40	122.90	105.60
2	2	22	Female	Normal	155	59	103.00	118.39	104.20
2	3	22	Female	Normal	155	59	106.60	119.34	106.80
2	4	22	Female	Slow	155	59	74.30	102.55	87.40
2	5	22	Female	Slow	155	59	83.20	108.91	92.30
2	6	22	Female	Slow	155	59	78.30	105.10	89.60
3	1	22	Female	Normal	163	54	126.30	134.27	113.70
3	2	22	Female	Normal	163	54	136.70	136.62	121.20
3	3	22	Female	Normal	163	54	141.00	142.04	119.40
3	4	22	Female	Slow	163	54	94.80	118.58	95.80
3	5	22	Female	Slow	163	54	103.80	127.52	97.60
3	6	22	Female	Slow	163	54	94.50	123.07	92.90
4	1	27	Female	Slow	150	37	93.27	117.95	94.90
4	2	27	Female	Slow	150	37	97.74	112.46	104.30
4	3	27	Female	Slow	150	37	100.93	113.41	106.80
4	4	27	Female	Normal	150	37	132.55	127.25	125.00
4	5	27	Female	Normal	150	37	128.42	124.78	123.50
4	6	27	Female	Normal	150	37	140.86	131.24	128.80

5	1	26	Female	Slow	168	53	87.93	122.26	86.30
5	2	26	Female	Slow	168	53	85.48	121.39	84.50
5	3	26	Female	Slow	168	53	90.85	123.18	88.50
5	4	26	Female	Normal	168	53	114.28	133.15	103.00
5	5	26	Female	Normal	168	53	111.69	135.65	98.80
5	6	26	Female	Normal	168	53	112.53	135.03	100.00
6	1	25	Female	Slow	157	43	114.83	132.11	104.30
6	2	25	Female	Slow	157	43	116.96	134.56	104.30
6	3	25	Female	Slow	157	43	115.73	133.16	104.30
6	4	25	Female	Normal	157	43	141.71	151.16	112.50
6	5	25	Female	Normal	157	43	142.91	148.61	115.40
6	6	25	Female	Normal	157	43	143.13	146.06	117.60
7	1	51	Female	Slow	152	42	92.42	114.57	96.80
7	2	51	Female	Slow	152	42	87.90	112.22	94.00
7	3	51	Female	Slow	152	42	91.42	113.33	96.80
7	4	51	Female	Normal	152	42	126.44	131.48	115.40
7	5	51	Female	Normal	152	42	126.29	131.32	115.40
7	6	51	Female	Normal	152	42	135.09	135.77	119.40
8	1	31	Female	Slow	165	65	52.08	108.13	57.80
8	2	31	Female	Slow	165	65	47.26	109.69	51.70
8	3	31	Female	Slow	165	65	37.71	98.80	45.80
8	4	31	Female	Normal	165	65	85.09	115.12	88.70
8	5	31	Female	Normal	165	65	97.68	123.52	94.90
8	6	31	Female	Normal	165	65	103.16	130.04	95.20
9	1	48	Female	Slow	158	43	72.64	106.05	82.20
9	2	48	Female	Slow	158	43	61.43	98.68	74.70
9	3	48	Female	Slow	158	43	65.54	101.75	77.30
9	4	48	Female	Normal	158	43	82.67	107.48	92.30
9	5	48	Female	Normal	158	43	85.89	109.88	93.80
9	6	48	Female	Normal	158	43	86.95	110.19	94.70
10	1	22	Female	Slow	153	45	93.04	111.98	99.70
10	2	22	Female	Slow	153	45	97.37	110.65	105.60

10	3	22	Female	Slow	153	45	95.49	108.83	105.30
10	4	22	Female	Normal	153	45	127.85	125.75	122.00
10	5	22	Female	Normal	153	45	122.66	123.69	119.00
10	6	22	Female	Normal	153	45	125.06	126.11	119.00
11	1	26	Female	Slow	156	48	83.02	107.94	92.30
11	2	26	Female	Slow	156	48	96.29	115.55	100.00
11	3	26	Female	Slow	156	48	88.07	108.95	97.00
11	4	26	Female	Normal	156	48	108.58	114.39	113.90
11	5	26	Female	Normal	156	48	116.53	119.32	117.20
11	6	26	Female	Normal	156	48	123.79	121.76	122.00
12	1	25	Female	Slow	165	52	108.19	131.54	98.70
12	2	25	Female	Slow	165	52	111.63	132.64	101.00
12	3	25	Female	Slow	165	52	101.53	125.86	96.80
12	4	25	Female	Normal	165	52	141.32	140.04	121.10
12	5	25	Female	Normal	165	52	140.48	143.96	117.10
12	6	25	Female	Normal	165	52	137.68	143.17	115.40
13	1	25	Male	Slow	175	70	86.43	103.10	100.60
13	2	25	Male	Slow	175	70	87.86	101.08	104.30
13	3	25	Male	Slow	175	70	87.62	100.81	104.30
13	4	25	Male	Normal	175	70	121.69	127.54	114.50
13	5	25	Male	Normal	175	70	112.69	122.16	110.70
13	6	25	Male	Normal	175	70	112.13	121.99	110.30
14	1	27	Female	Slow	162	50	116.35	132.10	105.70
14	2	27	Female	Slow	162	50	117.59	132.13	106.80
14	3	27	Female	Slow	162	50	110.42	129.90	102.00
14	4	27	Female	Normal	162	50	133.91	141.33	113.70
14	5	27	Female	Normal	162	50	130.18	139.35	112.10
14	6	27	Female	Normal	162	50	130.56	137.79	113.70
15	1	26	Female	Slow	174	59	88.58	105.67	100.60
15	2	26	Female	Slow	174	59	98.46	112.21	105.30
15	3	26	Female	Slow	174	59	93.09	105.19	106.20
15	4	26	Female	Normal	174	59	114.55	120.05	114.50

15	5	26	Female	Normal	174	59	136.58	132.71	123.50
15	6	26	Female	Normal	174	59	137.99	134.08	123.50
16	1	27	Male	Slow	189	77	83.86	120.09	83.80
16	2	27	Male	Slow	189	77	85.16	115.22	88.70
16	3	27	Male	Slow	189	77	91.29	120.12	91.20
16	4	27	Male	Normal	189	77	133.80	153.95	104.30
16	5	27	Male	Normal	189	77	129.67	149.19	104.30
16	6	27	Male	Normal	189	77	137.72	158.46	104.30
17	1	26	Male	Slow	170	65	99.54	121.03	98.70
17	2	26	Male	Slow	170	65	109.89	124.88	105.60
17	3	26	Male	Slow	170	65	108.70	120.90	107.90
17	4	26	Male	Normal	170	65	127.12	136.08	112.10
17	5	26	Male	Normal	170	65	124.51	131.99	113.20
17	6	26	Male	Normal	170	65	115.62	129.55	107.10
18	1	24	Male	Slow	185	75	95.82	139.38	82.50
18	2	24	Male	Slow	185	75	101.54	138.15	88.20
18	3	24	Male	Slow	185	75	104.53	138.46	90.60
18	4	24	Male	Normal	185	75	129.85	151.28	103.00
18	5	24	Male	Normal	185	75	130.81	149.92	104.70
18	6	24	Male	Normal	185	75	131.44	153.13	103.00
19	1	46	Male	Slow	178	50	104.62	121.77	103.10
19	2	46	Male	Slow	178	50	109.48	121.76	107.90
19	3	46	Male	Slow	178	50	105.94	115.26	110.30
19	4	46	Male	Normal	178	50	126.51	133.52	113.70
19	5	46	Male	Normal	178	50	127.94	133.04	115.40
19	6	46	Male	Normal	178	50	123.87	129.83	114.50
20	1	28	Male	Slow	180	82	88.84	129.23	82.50
20	2	28	Male	Slow	180	82	101.84	133.41	91.60
20	3	28	Male	Slow	180	82	90.23	126.64	85.50
20	4	28	Male	Normal	180	82	136.44	160.05	102.30
20	5	28	Male	Normal	180	82	138.52	161.39	103.00
20	6	28	Male	Normal	180	82	141.10	161.72	104.70

21	1	27	Male	Slow	174	76	79.16	112.42	84.50
21	2	27	Male	Slow	174	76	86.94	112.30	92.90
21	3	27	Male	Slow	174	76	99.26	119.12	100.00
21	4	27	Male	Normal	174	76	106.44	122.59	104.20
21	5	27	Male	Normal	174	76	107.46	122.11	105.60
21	6	27	Male	Normal	174	76	112.99	125.67	107.90
22	1	24	Male	Slow	170	60	83.14	106.14	94.00
22	2	24	Male	Slow	170	60	84.96	108.47	94.00
22	3	24	Male	Slow	170	60	83.85	108.20	93.00
22	4	24	Male	Normal	170	60	126.43	137.18	110.60
22	5	24	Male	Normal	170	60	133.03	137.86	115.80
22	6	24	Male	Normal	170	60	120.58	132.63	109.10
23	1	25	Male	Slow	172	63	79.75	117.14	81.70
23	2	25	Male	Slow	172	63	74.91	112.09	80.20
23	3	25	Male	Slow	172	63	80.44	115.19	83.80
23	4	25	Male	Normal	172	63	116.66	128.32	109.10
23	5	25	Male	Normal	172	63	115.69	134.79	103.00
23	6	25	Male	Normal	172	63	116.76	134.34	104.30
24	1	44	Male	Slow	168	67	65.79	88.91	88.80
24	2	44	Male	Slow	168	67	70.86	91.93	92.50
24	3	44	Male	Slow	168	67	70.86	91.93	92.50
24	4	44	Male	Normal	168	67	113.63	121.86	111.90
24	5	44	Male	Normal	168	67	111.18	120.96	110.30
24	6	44	Male	Normal	168	67	108.46	120.63	107.90
25	1	29	Male	Slow	165	62	79.65	116.99	81.70
25	2	29	Male	Slow	165	62	94.08	127.57	88.50
25	3	29	Male	Slow	165	62	80.80	114.48	84.70
25	4	29	Male	Normal	165	62	128.49	141.33	109.10
25	5	29	Male	Normal	165	62	122.72	134.98	109.10
25	6	29	Male	Normal	165	62	124.56	137.63	108.60
26	1	30	Male	Slow	170	60	77.08	116.20	79.60
26	2	30	Male	Slow	170	60	89.92	124.03	87.00

26	3	30	Male	Slow	170	60	87.99	119.31	88.50
26	4	30	Male	Normal	170	60	112.54	126.45	106.80
26	5	30	Male	Normal	170	60	116.46	128.10	109.10
26	6	30	Male	Normal	170	60	116.62	134.17	104.30
27	1	41	Male	Slow	174	74	69.46	103.55	80.50
27	2	41	Male	Slow	174	74	81.12	108.65	89.60
27	3	41	Male	Slow	174	74	78.35	109.46	85.90
27	4	41	Male	Normal	174	74	132.72	136.01	117.10
27	5	41	Male	Normal	174	74	136.01	137.16	119.00
27	6	41	Male	Normal	174	74	131.66	136.91	115.40
28	1	27	Female	Slow	165	52	95.60	120.88	94.90
28	2	27	Female	Slow	165	52	103.73	129.13	96.40
28	3	27	Female	Slow	165	52	99.37	123.18	96.80
28	4	27	Female	Normal	165	52	136.19	136.87	119.40
28	5	27	Female	Normal	165	52	133.30	133.97	119.40
28	6	27	Female	Normal	165	52	132.97	136.26	117.10
29	1	20	Male	Normal	160	55	90.70	119.95	91.20
29	2	20	Male	Normal	160	55	97.10	124.27	93.80
29	3	20	Male	Normal	160	55	78.60	113.42	83.30
29	4	20	Male	Slow	160	55	71.00	110.34	78.30
29	5	20	Male	Slow	160	55	66.90	113.79	72.30
29	6	20	Male	Slow	160	55	60.60	100.84	71.30
30	1	20	Male	Normal	180	85	92.30	141.19	80.00
30	2	20	Male	Normal	180	85	97.20	150.28	78.20
30	3	20	Male	Normal	180	85	99.30	148.22	80.80
30	4	20	Male	Slow	180	85	64.00	110.12	70.00
30	5	20	Male	Slow	180	85	63.00	112.74	67.60
30	6	20	Male	Slow	180	85	59.40	111.88	64.10
31	1	19	Male	Normal	170	72	109.90	135.58	97.60
31	2	19	Male	Normal	170	72	113.30	136.29	100.00
31	3	19	Male	Normal	170	72	114.70	136.31	101.70
31	4	19	Male	Slow	170	72	84.50	114.18	89.60

31	5	19	Male	Slow	170	72	93.20	121.92	92.00
31	6	19	Male	Slow	170	72	95.60	119.79	96.80
32	1	20	Male	Normal	170	64	105.80	126.32	100.00
32	2	20	Male	Normal	170	64	98.10	119.72	98.70
32	3	20	Male	Normal	170	64	102.70	126.77	97.70
32	4	20	Male	Slow	170	64	75.20	113.40	79.60
32	5	20	Male	Slow	170	64	78.20	115.02	81.70
32	6	20	Male	Slow	170	64	84.60	118.53	86.20
33	1	47	Female	Slow	166	51	81.96	116.39	84.50
33	2	47	Female	Slow	166	51	103.33	127.05	97.60
33	3	47	Female	Slow	166	51	98.41	119.65	98.70
33	4	47	Female	Normal	166	51	125.60	136.28	110.60
33	5	47	Female	Normal	166	51	122.55	139.14	105.70
33	6	47	Female	Normal	166	51	126.62	139.27	109.10
34	1	45	Male	Slow	175	78	71.30	112.44	76.10
34	2	45	Male	Slow	175	78	68.22	110.78	73.90
34	3	45	Male	Slow	175	78	70.63	110.64	76.60
34	4	45	Male	Normal	175	78	117.81	135.67	104.20
34	5	45	Male	Normal	175	78	124.95	141.86	105.70
34	6	45	Male	Normal	175	78	126.46	142.09	106.80
35	1	19	Male	Normal	169	63	89.90	116.75	92.00
35	2	19	Male	Normal	169	63	101.20	127.23	95.80
35	3	19	Male	Normal	169	63	99.30	127.10	93.80
35	4	19	Male	Slow	169	63	71.40	111.76	76.60
35	5	19	Male	Slow	169	63	74.40	112.79	79.60
35	6	19	Male	Slow	169	63	67.20	106.29	75.60
36	1	19	Male	Normal	170	53	105.30	130.58	96.80
36	2	19	Male	Normal	170	53	102.20	129.40	94.90
36	3	19	Male	Normal	170	53	96.50	126.24	91.20
36	4	19	Male	Slow	170	53	76.30	117.49	78.30
36	5	19	Male	Slow	170	53	85.80	126.38	81.70
36	6	19	Male	Slow	170	53	76.80	125.83	73.30

37	1	23	Male	Normal	168	60	90.60	119.48	91.20
37	2	23	Male	Normal	168	60	116.80	127.13	119.90
37	3	23	Male	Normal	168	60	102.80	120.98	102.00
37	4	23	Male	Slow	168	60	55.90	94.14	72.30
37	5	23	Male	Slow	168	60	56.90	93.62	73.40
37	6	23	Male	Slow	168	60	62.40	94.12	80.00
38	1	22	Male	Normal	162	60	103.80	126.63	98.70
38	2	22	Male	Normal	162	60	107.40	127.79	100.00
38	3	22	Male	Normal	162	60	104.40	135.29	93.80
38	4	22	Male	Slow	162	60	49.20	91.89	64.40
38	5	22	Male	Slow	162	60	48.00	91.25	63.50
38	6	22	Male	Slow	162	60	55.50	95.12	70.70
39	1	20	Male	Normal	169	69	144.20	143.63	121.20
39	2	20	Male	Normal	169	69	133.80	137.27	117.60
39	3	20	Male	Normal	169	69	127.90	128.42	119.40
39	4	20	Male	Slow	169	69	105.70	116.87	109.10
39	5	20	Male	Slow	169	69	104.70	119.95	104.50
39	6	20	Male	Slow	169	69	97.00	113.24	103.10
40	1	20	Female	Normal	172	58	95.80	117.71	96.80
40	2	20	Female	Normal	172	58	98.60	122.87	95.80
40	3	20	Female	Normal	172	58	98.00	124.80	94.90
40	4	20	Female	Slow	172	58	67.60	103.66	78.30
40	5	20	Female	Slow	172	58	60.30	98.48	73.60
40	6	20	Female	Slow	172	58	61.00	93.32	77.80
41	1	20	Female	Normal	153	53	95.90	118.63	97.70
41	2	20	Female	Normal	153	53	93.50	115.25	97.70
41	3	20	Female	Normal	153	53	90.00	114.81	94.90
41	4	20	Female	Slow	153	53	52.60	93.62	68.10
41	5	20	Female	Slow	153	53	50.70	92.89	64.70
41	6	20	Female	Slow	153	53	57.60	95.74	71.80
42	1	20	Female	Normal	155	48	113.80	127.28	107.10
42	2	20	Female	Normal	155	48	110.30	124.15	106.80

42	3	20	Female	Normal	155	48	116.70	128.40	109.10
42	4	20	Female	Slow	155	48	80.80	109.54	89.30
42	5	20	Female	Slow	155	48	83.60	109.83	92.30
42	6	20	Female	Slow	155	48	72.80	104.40	84.10
43	1	20	Female	Normal	156	51	111.70	118.88	113.20
43	2	20	Female	Normal	156	51	101.50	112.46	109.40
43	3	20	Female	Normal	156	51	99.50	112.66	106.20
43	4	20	Female	Slow	156	51	89.30	108.11	98.90
43	5	20	Female	Slow	156	51	78.90	103.29	91.60
43	6	20	Female	Slow	156	51	77.20	101.72	90.90
44	1	19	Female	Normal	163	64	117.20	128.86	110.30
44	2	19	Female	Normal	163	64	127.60	135.13	113.70
44	3	19	Female	Normal	163	64	120.40	132.78	109.10
44	4	19	Female	Slow	163	64	99.30	110.14	108.40
44	5	19	Female	Slow	163	64	97.20	113.24	103.10
44	6	19	Female	Slow	163	64	92.80	111.38	99.70
45	1	20	Female	Normal	152	56	101.20	118.27	103.10
45	2	20	Female	Normal	152	56	98.50	116.03	102.00
45	3	20	Female	Normal	152	56	97.60	114.14	102.00
45	4	20	Female	Slow	152	56	82.60	110.00	90.20
45	5	20	Female	Slow	152	56	92.10	112.55	98.10
45	6	20	Female	Slow	152	56	84.00	108.22	94.00
46	1	22	Female	Normal	164	49	115.30	131.47	105.70
46	2	22	Female	Normal	164	49	112.40	131.51	103.00
46	3	22	Female	Normal	164	49	114.00	129.55	105.70
46	4	22	Female	Slow	164	49	76.60	118.11	78.30
46	5	22	Female	Slow	164	49	79.80	118.46	80.90
46	6	22	Female	Slow	164	49	78.90	116.61	78.90
47	1	48	Male	Slow	168	75	80.94	98.21	98.90
47	2	48	Male	Slow	168	75	84.15	99.59	101.40
47	3	48	Male	Slow	168	75	91.42	101.11	108.50
47	4	48	Male	Normal	168	75	122.21	123.24	119.00

47	5	48	Male	Normal	168	75	121.56	121.06	120.50
47	6	48	Male	Normal	168	75	121.83	122.86	119.00
48	1	50	Female	Slow	150	44	110.71	113.36	117.20
48	2	50	Female	Slow	150	44	116.62	117.60	119.00
48	3	50	Female	Slow	150	44	107.40	108.85	118.40
48	4	50	Female	Normal	150	44	143.16	130.24	131.90
48	5	50	Female	Normal	150	44	149.28	133.58	134.10
48	6	50	Female	Normal	150	44	147.34	134.05	131.90
49	1	21	Male	Normal	180	75	116.80	148.51	95.20
49	2	21	Male	Normal	180	75	125.90	156.30	96.40
49	3	21	Male	Normal	180	75	124.50	156.41	96.40
49	4	21	Male	Slow	180	75	86.20	128.09	80.90
49	5	21	Male	Slow	180	75	86.90	128.21	80.90
49	6	21	Male	Slow	180	75	88.90	129.42	82.40
50	1	17	Male	Normal	167	65	102.60	133.31	92.70
50	2	17	Male	Normal	167	65	103.80	135.93	91.60
50	3	17	Male	Normal	167	65	103.60	135.01	92.70
50	4	17	Male	Slow	167	65	71.40	117.86	72.80
50	5	17	Male	Slow	167	65	75.50	121.15	74.40
50	6	17	Male	Slow	167	65	76.80	122.47	75.80

Appendix-B

Predicted Basis Gait Parameters using Trained GRNNs

Predicted Outcome for Normal Walking Speed

Subject	Age	Gender	Height (cm)	Weight (kg)	Speed (cm/s)	Stride length (cm)	Cadence (step/min)	Predicted Speed (cm/s)	MSE (cm/s)
1	48	Female	158	50	118.67	116.23	122.50	104.56	199.25
2	22	Female	155	59	105.72	120.21	105.53	104.84	0.79
3	22	Female	163	54	135.51	137.64	118.10	122.61	166.43
4	27	Female	150	37	133.95	127.76	125.77	131.07	8.28
5	26	Female	168	53	112.83	134.61	100.60	131.52	349.31
6	25	Female	157	43	142.59	148.61	115.17	120.03	508.85
7	51	Female	152	42	129.27	132.86	116.73	131.30	4.10
8	31	Female	165	65	95.31	122.89	92.93	127.54	1038.58
9	48	Female	158	43	85.17	109.18	93.60	126.71	1725.52
10	22	Female	153	45	125.19	125.18	120.00	116.39	77.44
11	26	Female	156	48	116.30	118.49	117.70	125.40	82.73
12	25	Female	165	52	139.83	142.39	117.87	125.02	219.17
13	25	Male	175	70	115.51	123.90	111.83	117.06	2.42
14	27	Female	162	50	131.55	139.49	113.17	128.17	11.40
15	26	Female	174	59	129.71	128.95	120.50	109.42	411.64
16	27	Male	189	77	133.74	153.87	104.30	130.89	8.12
17	26	Male	170	65	122.42	132.54	110.80	116.14	39.37
18	24	Male	185	75	130.70	151.44	103.57	127.76	8.65
19	46	Male	178	50	126.11	132.13	114.53	111.60	210.67
20	28	Male	180	82	138.69	161.05	103.33	116.76	480.93
21	27	Male	174	76	108.97	123.46	105.90	121.81	164.81
22	24	Male	170	60	126.68	135.89	111.83	111.52	230.01
23	25	Male	172	63	116.37	132.48	105.47	116.70	0.10
24	44	Male	168	67	111.09	121.15	110.03	126.00	222.26

25	29	Male	165	62	125.26	137.98	108.93	115.98	85.99
26	30	Male	170	60	115.21	129.57	106.73	120.71	30.29
27	41	Male	174	74	133.47	136.69	117.17	120.79	160.82
28	27	Female	165	52	134.15	135.70	118.63	127.18	48.53
29	20	Male	160	55	89.01	119.21	89.43	105.85	283.43
30	20	Male	180	85	97.29	146.56	79.67	127.72	926.35
31	19	Male	170	72	113.12	136.06	99.77	118.57	29.62
32	20	Male	170	64	102.32	124.27	98.80	112.61	105.88
33	47	Female	166	51	124.93	138.23	108.47	111.06	192.36
34	45	Male	175	78	123.07	139.87	105.57	129.56	42.06
35	19	Male	169	63	96.81	123.69	93.87	111.68	221.11
36	19	Male	170	53	101.20	128.74	94.30	107.91	44.96
37	23	Male	168	60	106.89	122.53	104.37	113.75	47.07
38	22	Male	162	60	105.47	129.90	97.50	104.51	0.90
39	20	Male	169	69	135.79	136.44	119.40	108.07	768.60
40	20	Female	172	58	97.25	121.79	95.83	126.71	867.86
41	20	Female	153	53	93.74	116.23	96.77	108.39	214.59
42	20	Female	155	48	113.61	126.61	107.67	111.91	2.88
43	20	Female	156	51	104.79	114.67	109.60	111.11	39.95
44	19	Female	163	64	122.40	132.26	111.03	117.74	21.72
45	20	Female	152	56	99.09	116.15	102.37	103.42	18.79
46	22	Female	164	49	114.26	130.84	104.80	129.93	245.34
47	48	Male	168	75	121.87	122.39	119.50	119.25	6.85
48	50	Female	150	44	146.59	132.62	132.63	122.76	567.94
49	21	Male	180	75	123.01	153.74	96.00	120.01	8.99
50	17	Male	167	65	103.68	134.75	92.33	109.77	37.07

Predicted Outcome for Slow Walking Speed

Subject	Age	Gender	Height (cm)	Weight (kg)	Speed (cm/s)	Stride length (cm)	Cadence (steps/min)	Predicted Speed (cm/s)	MSE (cm/s)
1	48	Female	158	50	118.67	116.23	122.50	104.56	199.25

2	22	Female	155	59	105.72	120.21	105.53	104.84	0.79
3	22	Female	163	54	135.51	137.64	118.10	122.61	166.43
4	27	Female	150	37	133.95	127.76	125.77	131.07	8.28
5	26	Female	168	53	112.83	134.61	100.60	131.52	349.31
6	25	Female	157	43	142.59	148.61	115.17	120.03	508.85
7	51	Female	152	42	129.27	132.86	116.73	131.30	4.10
8	31	Female	165	65	95.31	122.89	92.93	127.54	1038.58
9	48	Female	158	43	85.17	109.18	93.60	126.71	1725.52
10	22	Female	153	45	125.19	125.18	120.00	116.39	77.44
11	26	Female	156	48	116.30	118.49	117.70	125.40	82.73
12	25	Female	165	52	139.83	142.39	117.87	125.02	219.17
13	25	Male	175	70	115.51	123.90	111.83	117.06	2.42
14	27	Female	162	50	131.55	139.49	113.17	128.17	11.40
15	26	Female	174	59	129.71	128.95	120.50	109.42	411.64
16	27	Male	189	77	133.74	153.87	104.30	130.89	8.12
17	26	Male	170	65	122.42	132.54	110.80	116.14	39.37
18	24	Male	185	75	130.70	151.44	103.57	127.76	8.65
19	46	Male	178	50	126.11	132.13	114.53	111.60	210.67
20	28	Male	180	82	138.69	161.05	103.33	116.76	480.93
21	27	Male	174	76	108.97	123.46	105.90	121.81	164.81
22	24	Male	170	60	126.68	135.89	111.83	111.52	230.01
23	25	Male	172	63	116.37	132.48	105.47	116.70	0.10
24	44	Male	168	67	111.09	121.15	110.03	126.00	222.26
25	29	Male	165	62	125.26	137.98	108.93	115.98	85.99
26	30	Male	170	60	115.21	129.57	106.73	120.71	30.29
27	41	Male	174	74	133.47	136.69	117.17	120.79	160.82
28	27	Female	165	52	134.15	135.70	118.63	127.18	48.53
29	20	Male	160	55	89.01	119.21	89.43	105.85	283.43
30	20	Male	180	85	97.29	146.56	79.67	127.72	926.35
31	19	Male	170	72	113.12	136.06	99.77	118.57	29.62
32	20	Male	170	64	102.32	124.27	98.80	112.61	105.88
33	47	Female	166	51	124.93	138.23	108.47	111.06	192.36

34	45	Male	175	78	123.07	139.87	105.57	129.56	42.06
35	19	Male	169	63	96.81	123.69	93.87	111.68	221.11
36	19	Male	170	53	101.20	128.74	94.30	107.91	44.96
37	23	Male	168	60	106.89	122.53	104.37	113.75	47.07
38	22	Male	162	60	105.47	129.90	97.50	104.51	0.90
39	20	Male	169	69	135.79	136.44	119.40	108.07	768.60
40	20	Female	172	58	97.25	121.79	95.83	126.71	867.86
41	20	Female	153	53	93.74	116.23	96.77	108.39	214.59
42	20	Female	155	48	113.61	126.61	107.67	111.91	2.88
43	20	Female	156	51	104.79	114.67	109.60	111.11	39.95
44	19	Female	163	64	122.40	132.26	111.03	117.74	21.72
45	20	Female	152	56	99.09	116.15	102.37	103.42	18.79
46	22	Female	164	49	114.26	130.84	104.80	129.93	245.34
47	48	Male	168	75	121.87	122.39	119.50	119.25	6.85
48	50	Female	150	44	146.59	132.62	132.63	122.76	567.94
49	21	Male	180	75	123.01	153.74	96.00	120.01	8.99
50	17	Male	167	65	103.68	134.75	92.33	109.77	37.07

Predicted Outcomes of Stride Length for Normal Walking Speed

Subject	Age	Gender	Height (cm)	Weight (kg)	Speed (cm/s)	Stride length (cm)	Cadence (step/min)	Predicted Stride Length (cm)	MSE (cm)
1	48	Female	158	50	114.54	114.06	120.50	128.67	213.36
1	48	Female	158	50	119.56	116.17	123.50	130.76	212.73
1	48	Female	158	50	121.93	118.47	123.50	132.22	189.18
2	22	Female	155	59	102.80	118.39	104.20	126.13	59.93
2	22	Female	155	59	106.21	119.34	106.80	126.36	49.28
2	22	Female	155	59	108.15	122.90	105.60	126.48	12.80
3	22	Female	163	54	127.22	134.27	113.70	135.75	2.19
3	22	Female	163	54	137.99	136.62	121.20	142.69	36.85
3	22	Female	163	54	141.33	142.04	119.40	143.36	1.75
4	27	Female	150	37	128.42	124.78	123.50	136.86	146.04

4	27	Female	150	37	132.55	127.25	125.00	139.70	154.89
4	27	Female	150	37	140.86	131.24	128.80	143.90	160.31
5	26	Female	168	53	111.69	135.65	98.80	127.01	74.58
5	26	Female	168	53	112.53	135.03	100.00	127.33	59.33
5	26	Female	168	53	114.29	133.15	103.00	128.01	26.39
6	25	Female	157	43	141.71	151.16	112.50	142.84	69.17
6	25	Female	157	43	142.91	148.61	115.40	142.86	33.02
6	25	Female	157	43	143.14	146.06	117.60	142.99	9.41
7	51	Female	152	42	126.29	131.32	115.40	135.15	14.64
7	51	Female	152	42	126.44	131.48	115.40	135.26	14.25
7	51	Female	152	42	135.09	135.77	119.40	141.10	28.40
8	31	Female	165	65	85.09	115.12	88.70	114.03	1.19
8	31	Female	165	65	97.68	123.52	94.90	124.90	1.91
8	31	Female	165	65	103.17	130.04	95.20	125.74	18.46
9	48	Female	158	43	82.67	107.48	92.30	113.94	41.72
9	48	Female	158	43	85.89	109.88	93.80	115.68	33.69
9	48	Female	158	43	86.96	110.19	94.70	116.75	42.99
10	22	Female	153	45	122.66	123.69	119.00	132.61	79.65
10	22	Female	153	45	125.06	126.11	119.00	134.37	68.20
10	22	Female	153	45	127.85	125.75	122.00	136.43	114.03
11	26	Female	156	48	108.58	114.39	113.90	126.85	155.29
11	26	Female	156	48	116.54	119.32	117.20	129.25	98.58
11	26	Female	156	48	123.79	121.76	122.00	133.52	138.33
12	25	Female	165	52	137.68	143.17	115.40	142.26	0.82
12	25	Female	165	52	140.48	143.96	117.10	143.16	0.65
12	25	Female	165	52	141.32	140.04	121.10	143.48	11.80
13	25	Male	175	70	112.13	121.99	110.30	127.59	31.39
13	25	Male	175	70	112.69	122.16	110.70	127.78	31.58
13	25	Male	175	70	121.69	127.54	114.50	131.80	18.15
14	27	Female	162	50	130.18	139.35	112.10	137.68	2.78
14	27	Female	162	50	130.56	137.79	113.70	137.99	0.04
14	27	Female	162	50	133.91	141.33	113.70	140.14	1.42

15	26	Female	174	59	114.55	120.05	114.50	128.49	71.30
15	26	Female	174	59	136.58	132.71	123.50	142.12	88.57
15	26	Female	174	59	137.99	134.08	123.50	142.80	76.10
16	27	Male	189	77	129.67	149.19	104.30	137.05	147.30
16	27	Male	189	77	133.81	153.95	104.30	139.63	205.02
16	27	Male	189	77	137.73	158.46	104.30	141.63	283.33
17	26	Male	170	65	115.62	129.55	107.10	128.60	0.90
17	26	Male	170	65	124.51	131.99	113.20	133.79	3.25
17	26	Male	170	65	127.12	136.08	112.10	135.63	0.20
18	24	Male	185	75	129.85	151.28	103.00	137.11	200.69
18	24	Male	185	75	130.81	149.92	104.70	137.80	146.97
18	24	Male	185	75	131.44	153.13	103.00	138.12	225.33
19	46	Male	178	50	123.88	129.83	114.50	133.37	12.53
19	46	Male	178	50	126.51	133.52	113.70	135.25	3.00
19	46	Male	178	50	127.94	133.04	115.40	136.30	10.61
20	28	Male	180	82	136.44	160.05	102.30	140.95	364.88
20	28	Male	180	82	138.53	161.39	103.00	141.81	383.54
20	28	Male	180	82	141.10	161.72	104.70	142.25	379.01
21	27	Male	174	76	106.45	122.59	104.20	126.27	13.51
21	27	Male	174	76	107.46	122.11	105.60	126.40	18.39
21	27	Male	174	76	113.00	125.67	107.90	127.78	4.45
22	24	Male	170	60	120.58	132.63	109.10	130.89	3.01
22	24	Male	170	60	126.43	137.18	110.60	135.10	4.33
22	24	Male	170	60	133.03	137.86	115.80	139.68	3.30
23	25	Male	172	63	115.69	134.79	103.00	128.48	39.88
23	25	Male	172	63	116.66	128.32	109.10	129.03	0.51
23	25	Male	172	63	116.76	134.34	104.30	128.90	29.63
24	44	Male	168	67	108.47	120.63	107.90	126.61	35.82
24	44	Male	168	67	111.18	120.96	110.30	127.31	40.37
24	44	Male	168	67	113.63	121.86	111.90	128.12	39.16
25	29	Male	165	62	122.72	134.98	109.10	132.34	6.95
25	29	Male	165	62	124.56	137.63	108.60	133.68	15.64

25	29	Male	165	62	128.49	141.33	109.10	136.46	23.71
26	30	Male	170	60	112.54	126.45	106.80	127.60	1.31
26	30	Male	170	60	116.46	128.10	109.10	128.96	0.74
26	30	Male	170	60	116.62	134.17	104.30	128.84	28.37
27	41	Male	174	74	131.66	136.91	115.40	138.77	3.47
27	41	Male	174	74	132.72	136.01	117.10	139.53	12.36
27	41	Male	174	74	136.02	137.16	119.00	141.62	19.85
28	27	Female	165	52	132.97	136.26	117.10	139.68	11.72
28	27	Female	165	52	133.30	133.97	119.40	139.98	36.18
28	27	Female	165	52	136.19	136.87	119.40	141.73	23.59
29	20	Male	160	55	78.73	113.42	83.30	110.78	6.96
29	20	Male	160	55	91.16	119.95	91.20	120.69	0.55
29	20	Male	160	55	97.14	124.27	93.80	124.68	0.17
30	20	Male	180	85	94.13	141.19	80.00	122.07	365.74
30	20	Male	180	85	97.93	150.28	78.20	123.82	699.97
30	20	Male	180	85	99.80	148.22	80.80	124.51	562.24
31	19	Male	170	72	110.27	135.58	97.60	126.56	81.42
31	19	Male	170	72	113.58	136.29	100.00	127.66	74.41
31	19	Male	170	72	115.52	136.31	101.70	128.37	63.09
32	20	Male	170	64	98.47	119.72	98.70	125.30	31.18
32	20	Male	170	64	103.21	126.77	97.70	125.87	0.82
32	20	Male	170	64	105.27	126.32	100.00	126.04	0.08
33	47	Female	166	51	122.56	139.14	105.70	132.11	49.47
33	47	Female	166	51	125.60	136.28	110.60	134.51	3.14
33	47	Female	166	51	126.62	139.27	109.10	135.18	16.74
34	45	Male	175	78	117.81	135.67	104.20	129.30	40.63
34	45	Male	175	78	124.96	141.86	105.70	133.87	63.89
34	45	Male	175	78	126.46	142.09	106.80	134.99	50.45
35	19	Male	169	63	89.51	116.75	92.00	119.02	5.15
35	19	Male	169	63	99.35	127.10	93.80	125.23	3.50
35	19	Male	169	63	101.57	127.23	95.80	125.66	2.48
36	19	Male	170	53	95.94	126.24	91.20	124.07	4.72

36	19	Male	170	53	102.33	129.40	94.90	125.68	13.85
36	19	Male	170	53	105.33	130.58	96.80	125.89	22.00
37	23	Male	168	60	90.80	119.48	91.20	120.32	0.71
37	23	Male	168	60	102.83	120.98	102.00	126.04	25.60
37	23	Male	168	60	127.02	127.13	119.90	135.80	75.14
38	22	Male	162	60	104.15	126.63	98.70	125.95	0.46
38	22	Male	162	60	105.75	135.29	93.80	125.75	90.99
38	22	Male	162	60	106.49	127.79	100.00	126.08	2.91
39	20	Male	169	69	127.78	128.42	119.40	136.31	62.21
39	20	Male	169	69	134.52	137.27	117.60	140.68	11.64
39	20	Male	169	69	145.07	143.63	121.20	142.53	1.20
40	20	Female	172	58	94.95	117.71	96.80	124.00	39.62
40	20	Female	172	58	98.09	122.87	95.80	125.06	4.80
40	20	Female	172	58	98.70	124.80	94.90	125.15	0.13
41	20	Female	153	53	90.80	114.81	94.90	120.73	35.06
41	20	Female	153	53	93.83	115.25	97.70	123.45	67.31
41	20	Female	153	53	96.58	118.63	97.70	124.73	37.19
42	20	Female	155	48	110.49	124.15	106.80	127.00	8.11
42	20	Female	155	48	113.60	127.28	107.10	127.94	0.44
42	20	Female	155	48	116.74	128.40	109.10	129.06	0.44
43	20	Female	156	51	99.70	112.66	106.20	125.88	174.82
43	20	Female	156	51	102.53	112.46	109.40	126.32	192.06
43	20	Female	156	51	112.14	118.88	113.20	127.69	77.68
44	19	Female	163	64	118.44	128.86	110.30	129.79	0.87
44	19	Female	163	64	120.72	132.78	109.10	130.98	3.24
44	19	Female	163	64	128.04	135.13	113.70	136.31	1.39
45	20	Female	152	56	97.02	114.14	102.00	125.10	120.15
45	20	Female	152	56	98.63	116.03	102.00	125.50	89.66
45	20	Female	152	56	101.61	118.27	103.10	125.99	59.66
46	22	Female	164	49	112.88	131.51	103.00	127.56	15.60
46	22	Female	164	49	114.11	129.55	105.70	128.06	2.23
46	22	Female	164	49	115.80	131.47	105.70	128.61	8.16

47	48	Male	168	75	121.56	121.06	120.50	131.89	117.37
47	48	Male	168	75	121.84	122.86	119.00	132.04	84.18
47	48	Male	168	75	122.21	123.24	119.00	132.30	82.03
48	50	Female	150	44	143.16	130.24	131.90	144.09	191.87
48	50	Female	150	44	147.34	134.05	131.90	142.48	71.05
48	50	Female	150	44	149.28	133.58	134.10	141.59	64.20
49	21	Male	180	75	117.82	148.51	95.20	128.92	383.71
49	21	Male	180	75	125.56	156.30	96.40	133.94	499.96
49	21	Male	180	75	125.65	156.41	96.40	134.00	502.04
50	17	Male	167	65	102.98	133.31	92.70	125.61	59.33
50	17	Male	167	65	103.76	135.93	91.60	125.58	107.06
50	17	Male	167	65	104.30	135.01	92.70	125.66	87.48

Predicted Outcome of Stride Length for Slow Walking Speed

Subject	Age	Gender	Height (cm)	Weight (kg)	Speed (cm/s)	Stride length (cm)	Cadence (steps/min)	Predicted Stride Length (cm)	MSE (cm)
1	48	Female	158	50	83.60	98.94	101.40	107.71	76.93
1	48	Female	158	50	93.21	101.32	110.40	111.62	106.14
1	48	Female	158	50	101.74	108.14	112.90	113.18	25.35
2	22	Female	155	59	74.69	102.55	87.40	104.07	2.30
2	22	Female	155	59	78.47	105.10	89.60	105.09	0.00
2	22	Female	155	59	83.77	108.91	92.30	108.10	0.66
3	22	Female	163	54	94.67	118.58	95.80	118.08	0.25
3	22	Female	163	54	95.28	123.07	92.90	116.91	37.90
3	22	Female	163	54	103.72	127.52	97.60	122.74	22.83
4	27	Female	150	37	93.28	117.95	94.90	112.78	26.69
4	27	Female	150	37	97.75	112.46	104.30	113.89	2.06
4	27	Female	150	37	100.93	113.41	106.80	112.06	1.83
5	26	Female	168	53	85.48	121.39	84.50	112.51	78.77
5	26	Female	168	53	87.93	122.26	86.30	115.11	51.13
5	26	Female	168	53	90.85	123.18	88.50	114.91	68.35

6	25	Female	157	43	114.83	132.11	104.30	133.78	2.79
6	25	Female	157	43	115.74	133.16	104.30	133.31	0.02
6	25	Female	157	43	116.96	134.56	104.30	132.67	3.55
7	51	Female	152	42	87.91	112.22	94.00	111.57	0.42
7	51	Female	152	42	91.42	113.33	96.80	112.82	0.26
7	51	Female	152	42	92.42	114.57	96.80	112.50	4.27
8	31	Female	165	65	37.71	98.80	45.80	108.71	98.29
8	31	Female	165	65	47.26	109.69	51.70	100.68	81.16
8	31	Female	165	65	52.08	108.13	57.80	101.44	44.74
9	48	Female	158	43	61.43	98.68	74.70	101.70	9.12
9	48	Female	158	43	65.54	101.75	77.30	104.56	7.91
9	48	Female	158	43	72.64	106.05	82.20	107.27	1.49
10	22	Female	153	45	93.04	111.98	99.70	112.31	0.11
10	22	Female	153	45	95.50	108.83	105.30	112.56	13.93
10	22	Female	153	45	97.37	110.65	105.60	111.54	0.80
11	26	Female	156	48	83.02	107.94	92.30	107.01	0.86
11	26	Female	156	48	88.07	108.95	97.00	107.96	0.99
11	26	Female	156	48	96.29	115.55	100.00	107.12	71.11
12	25	Female	165	52	101.53	125.86	96.80	123.52	5.49
12	25	Female	165	52	108.19	131.54	98.70	129.29	5.08
12	25	Female	165	52	111.64	132.64	101.00	130.82	3.32
13	25	Male	175	70	86.43	103.10	100.60	105.23	4.52
13	25	Male	175	70	87.62	100.81	104.30	105.48	21.79
13	25	Male	175	70	87.86	101.08	104.30	105.37	18.43
14	27	Female	162	50	110.42	129.90	102.00	131.31	1.99
14	27	Female	162	50	116.36	132.10	105.70	131.86	0.06
14	27	Female	162	50	117.60	132.13	106.80	131.98	0.02
15	26	Female	174	59	88.59	105.67	100.60	105.38	0.08
15	26	Female	174	59	93.09	105.19	106.20	108.24	9.32
15	26	Female	174	59	98.46	112.21	105.30	116.70	20.17
16	27	Male	189	77	83.86	120.09	83.80	115.48	21.22
16	27	Male	189	77	85.17	115.22	88.70	120.09	23.77

16	27	Male	189	77	91.29	120.12	91.20	117.65	6.08
17	26	Male	170	65	99.55	121.03	98.70	117.52	12.29
17	26	Male	170	65	108.71	120.90	107.90	121.54	0.41
17	26	Male	170	65	109.89	124.88	105.60	119.80	25.82
18	24	Male	185	75	95.82	139.38	82.50	137.28	4.42
18	24	Male	185	75	101.54	138.15	88.20	138.64	0.24
18	24	Male	185	75	104.54	138.46	90.60	138.16	0.09
19	46	Male	178	50	104.62	121.77	103.10	119.83	3.78
19	46	Male	178	50	105.94	115.26	110.30	122.96	59.28
19	46	Male	178	50	109.48	121.76	107.90	117.92	14.76
20	28	Male	180	82	88.85	129.23	82.50	128.05	1.40
20	28	Male	180	82	90.23	126.64	85.50	128.86	4.94
20	28	Male	180	82	101.84	133.41	91.60	119.68	188.61
21	27	Male	174	76	79.16	112.42	84.50	111.25	1.37
21	27	Male	174	76	86.94	112.30	92.90	104.10	67.23
21	27	Male	174	76	99.27	119.12	100.00	111.84	52.95
22	24	Male	170	60	83.14	106.14	94.00	113.98	61.49
22	24	Male	170	60	83.86	108.20	93.00	114.12	34.99
22	24	Male	170	60	84.97	108.47	94.00	115.07	43.62
23	25	Male	172	63	74.91	112.09	80.20	114.88	7.79
23	25	Male	172	63	79.75	117.14	81.70	113.59	12.60
23	25	Male	172	63	80.44	115.19	83.80	113.70	2.22
24	44	Male	168	67	65.79	88.91	88.80	100.69	138.71
24	44	Male	168	67	70.86	91.93	92.50	107.70	248.69
24	44	Male	168	67	70.86	91.93	92.50	107.70	248.69
25	29	Male	165	62	79.65	116.99	81.70	116.51	0.23
25	29	Male	165	62	80.80	114.48	84.70	116.68	4.83
25	29	Male	165	62	94.08	127.57	88.50	118.53	81.77
26	30	Male	170	60	77.08	116.20	79.60	115.58	0.38
26	30	Male	170	60	87.99	119.31	88.50	116.81	6.27
26	30	Male	170	60	89.92	124.03	87.00	117.21	46.55
27	41	Male	174	74	69.46	103.55	80.50	110.23	44.66

27	41	Male	174	74	78.36	109.46	85.90	112.42	8.78
27	41	Male	174	74	81.13	108.65	89.60	111.51	8.21
28	27	Female	165	52	95.60	120.88	94.90	120.77	0.01
28	27	Female	165	52	99.37	123.18	96.80	121.67	2.27
28	27	Female	165	52	103.73	129.13	96.40	125.31	14.60
29	20	Male	160	55	59.92	100.84	71.30	98.45	5.71
29	20	Male	160	55	68.56	113.79	72.30	106.97	46.45
29	20	Male	160	55	72.00	110.34	78.30	110.07	0.07
30	20	Male	180	85	59.76	111.88	64.10	111.64	0.06
30	20	Male	180	85	63.51	112.74	67.60	110.69	4.18
30	20	Male	180	85	64.24	110.12	70.00	112.51	5.73
31	19	Male	170	72	85.25	114.18	89.60	114.61	0.18
31	19	Male	170	72	93.47	121.92	92.00	117.60	18.66
31	19	Male	170	72	96.63	119.79	96.80	117.88	3.63
32	20	Male	170	64	75.22	113.40	79.60	115.25	3.43
32	20	Male	170	64	78.31	115.02	81.70	115.32	0.09
32	20	Male	170	64	85.14	118.53	86.20	113.91	21.38
33	47	Female	166	51	81.96	116.39	84.50	113.49	8.40
33	47	Female	166	51	98.41	119.65	98.70	122.59	8.65
33	47	Female	166	51	103.33	127.05	97.60	125.31	3.04
34	45	Male	175	78	68.22	110.78	73.90	108.32	6.04
34	45	Male	175	78	70.63	110.64	76.60	109.16	2.19
34	45	Male	175	78	71.31	112.44	76.10	108.63	14.53
35	19	Male	169	63	66.96	106.29	75.60	97.02	86.01
35	19	Male	169	63	71.34	111.76	76.60	105.36	40.98
35	19	Male	169	63	74.82	112.79	79.60	113.70	0.82
36	19	Male	170	53	76.66	117.49	78.30	115.36	4.56
36	19	Male	170	53	76.86	125.83	73.30	114.05	138.73
36	19	Male	170	53	86.04	126.38	81.70	113.79	158.55
37	23	Male	168	60	56.72	94.14	72.30	94.23	0.01
37	23	Male	168	60	57.26	93.62	73.40	94.50	0.77
37	23	Male	168	60	62.75	94.12	80.00	94.91	0.62

38	22	Male	162	60	48.29	91.25	63.50	94.74	12.21
38	22	Male	162	60	49.31	91.89	64.40	94.32	5.91
38	22	Male	162	60	56.04	95.12	70.70	98.84	13.80
39	20	Male	169	69	97.29	113.24	103.10	119.80	43.03
39	20	Male	169	69	104.46	119.95	104.50	119.79	0.02
39	20	Male	169	69	106.25	116.87	109.10	121.72	23.52
40	20	Female	172	58	60.40	98.48	73.60	94.16	18.69
40	20	Female	172	58	60.50	93.32	77.80	98.72	29.15
40	20	Female	172	58	67.64	103.66	78.30	105.59	3.73
41	20	Female	153	53	50.08	92.89	64.70	93.82	0.86
41	20	Female	153	53	53.13	93.62	68.10	94.01	0.16
41	20	Female	153	53	57.28	95.74	71.80	93.54	4.84
42	20	Female	155	48	73.17	104.40	84.10	103.16	1.54
42	20	Female	155	48	81.52	109.54	89.30	106.69	8.13
42	20	Female	155	48	84.48	109.83	92.30	108.09	3.02
43	20	Female	156	51	77.05	101.72	90.90	104.72	9.03
43	20	Female	156	51	78.84	103.29	91.60	105.31	4.06
43	20	Female	156	51	89.10	108.11	98.90	108.42	0.09
44	19	Female	163	64	92.54	111.38	99.70	120.45	82.35
44	19	Female	163	64	97.29	113.24	103.10	119.13	34.73
44	19	Female	163	64	99.49	110.14	108.40	121.12	120.64
45	20	Female	152	56	82.68	110.00	90.20	109.04	0.92
45	20	Female	152	56	84.77	108.22	94.00	110.84	6.85
45	20	Female	152	56	92.01	112.55	98.10	113.00	0.20
46	22	Female	164	49	76.67	116.61	78.90	117.64	1.05
46	22	Female	164	49	77.07	118.11	78.30	117.08	1.06
46	22	Female	164	49	79.86	118.46	80.90	116.51	3.79
47	48	Male	168	75	80.94	98.21	98.90	114.20	255.56
47	48	Male	168	75	84.15	99.59	101.40	114.72	228.80
47	48	Male	168	75	91.42	101.11	108.50	121.30	407.78
48	50	Female	150	44	107.40	108.85	118.40	113.42	20.90
48	50	Female	150	44	110.71	113.36	117.20	110.78	6.68

48	50	Female	150	44	116.62	117.60	119.00	113.08	20.44
49	21	Male	180	75	86.35	128.09	80.90	128.42	0.11
49	21	Male	180	75	86.43	128.21	80.90	128.38	0.03
49	21	Male	180	75	88.87	129.42	82.40	127.99	2.05
50	17	Male	167	65	71.50	117.86	72.80	103.66	201.58
50	17	Male	167	65	75.11	121.15	74.40	112.67	71.88
50	17	Male	167	65	77.36	122.47	75.80	113.96	72.49

Appendix-C

Detailed Mathematics Used in Lower Limb Angles Calculation

In this section, the computation of lower limb joint angles with the coordinate of fifteen markers is described. The reference systems, uvw , are first computed for each segment, to predict the positions of joint centers and segment endpoints. Segment reference frames (xyz) are generated with the joint centre positions and the external marker positions. The external landmark positions were obtained from motion capture experiment and the length units is in mm. The segment reference frames are embedded at the centre of gravity of each segment **Figure C-1**.

Figure C-1: Embedment of segment reference frames (xyz) at the centre of gravity of each segment

The unit vectors for the right foot are defined as

$$\begin{aligned}
\mathbf{u}_{Foot,r} &= (\mathbf{P}_1 - \mathbf{P}_2) / |\mathbf{P}_1 - \mathbf{P}_2| \\
\mathbf{w}_{Foot,r} &= \frac{(\mathbf{P}_1 - \mathbf{P}_3) \times (\mathbf{P}_1 - \mathbf{P}_3)}{|(\mathbf{P}_1 - \mathbf{P}_3) \times (\mathbf{P}_1 - \mathbf{P}_3)|} \\
\mathbf{v}_{Foot,r} &= \mathbf{w}_{Foot,r} \times \mathbf{u}_{Foot,r}
\end{aligned} \tag{C.1}$$

The position of the right ankle ($\mathbf{P}_{Ankle,r}$) and right toe ($\mathbf{P}_{Toe,r}$) can be obtained by

$$\mathbf{P}_{Ankle,r} = \mathbf{P}_3 + 0.016A_{13}\mathbf{u}_{Foot,r} + 0.392A_{15}\mathbf{v}_{Foot,r} + 0.478A_{17}\mathbf{w}_{Foot,r} \tag{C.2}$$

$$\mathbf{P}_{Toe,r} = \mathbf{P}_3 + 0.742A_{13}\mathbf{u}_{Foot,r} + 1.074A_{15}\mathbf{v}_{Foot,r} - 0.187A_{19}\mathbf{w}_{Foot,r} \tag{C.3}$$

The unit vectors for the left foot are defined as

$$\begin{aligned}
\mathbf{u}_{Foot,l} &= (\mathbf{P}_8 - \mathbf{P}_9) / |\mathbf{P}_8 - \mathbf{P}_9| \\
\mathbf{w}_{Foot,l} &= \frac{(\mathbf{P}_8 - \mathbf{P}_{10}) \times (\mathbf{P}_9 - \mathbf{P}_{10})}{|(\mathbf{P}_8 - \mathbf{P}_{10}) \times (\mathbf{P}_9 - \mathbf{P}_{10})|} \\
\mathbf{v}_{Foot,l} &= \mathbf{w}_{Foot,l} \times \mathbf{u}_{Foot,l}
\end{aligned} \tag{C.4}$$

The position of the left ankle ($\mathbf{P}_{Ankle,l}$) and left toe ($\mathbf{P}_{Toe,l}$) can be obtained by

$$\mathbf{P}_{Ankle,l} = \mathbf{P}_{10} + 0.016A_{14}\mathbf{u}_{Foot,l} + 0.392A_{16}\mathbf{v}_{Foot,l} - 0.478A_{18}\mathbf{w}_{Foot,l} \tag{C.5}$$

$$\mathbf{P}_{Toe,l} = \mathbf{P}_{10} + 0.742A_{14}\mathbf{u}_{Foot,l} + 1.074A_{16}\mathbf{v}_{Foot,l} + 0.187A_{20}\mathbf{w}_{Foot,l} \tag{C.6}$$

The unit vectors for the right calf are defined as

$$\begin{aligned}
\mathbf{v}_{Calf,r} &= (\mathbf{P}_3 - \mathbf{P}_5) / |\mathbf{P}_3 - \mathbf{P}_5| \\
\mathbf{u}_{Calf,r} &= \frac{(\mathbf{P}_4 - \mathbf{P}_5) \times (\mathbf{P}_3 - \mathbf{P}_5)}{|(\mathbf{P}_4 - \mathbf{P}_5) \times (\mathbf{P}_3 - \mathbf{P}_5)|} \\
\mathbf{w}_{Calf,r} &= \mathbf{u}_{Calf,r} \times \mathbf{v}_{Calf,r}
\end{aligned} \tag{C.7}$$

The position of the right knee ($\mathbf{P}_{Knee,r}$) can be obtained by

$$\begin{aligned}
\mathbf{P}_{Knee,r} &= \mathbf{P}_5 + 0.000A_{11}\mathbf{u}_{Calf,r} + 0.000A_{11}\mathbf{v}_{Calf,r} + 0.5A_{11}\mathbf{w}_{Calf,r} \\
&= \mathbf{P}_5 + 0.5A_{11}\mathbf{w}_{Calf,r}
\end{aligned} \tag{C.8}$$

The unit vectors for the left calf are defined as

$$\begin{aligned}
\mathbf{v}_{Calf,l} &= (\mathbf{P}_{10} - \mathbf{P}_{12}) / |\mathbf{P}_{10} - \mathbf{P}_{12}| \\
\mathbf{w}_{Calf,l} &= \frac{(\mathbf{P}_{11} - \mathbf{P}_{12}) \times (\mathbf{P}_{10} - \mathbf{P}_{12})}{|(\mathbf{P}_{11} - \mathbf{P}_{12}) \times (\mathbf{P}_{10} - \mathbf{P}_{12})|} \\
\mathbf{u}_{Calf,l} &= \mathbf{w}_{Calf,l} \times \mathbf{v}_{Calf,l}
\end{aligned} \tag{C.9}$$

The position of the left knee ($\mathbf{P}_{Knee,l}$) can be obtained by

$$\begin{aligned}\mathbf{P}_{Knee,l} &= \mathbf{P}_{12} + 0.000A_{12}\mathbf{u}_{Calf,l} + 0.000A_{12}\mathbf{v}_{Calf,l} - 0.5A_{12}\mathbf{w}_{Calf,l} \\ &= \mathbf{P}_{12} - 0.5A_{12}\mathbf{w}_{Calf,l}\end{aligned}\quad (C.10)$$

The unit vectors for the pelvis are defined as

$$\begin{aligned}\mathbf{v}_{Pelvis} &= (\mathbf{P}_{14} - \mathbf{P}_7) / |\mathbf{P}_{14} - \mathbf{P}_7| \\ \mathbf{w}_{Pelvis} &= \frac{(\mathbf{P}_7 - \mathbf{P}_{15}) \times (\mathbf{P}_{14} - \mathbf{P}_{15})}{|(\mathbf{P}_7 - \mathbf{P}_{15}) \times (\mathbf{P}_{14} - \mathbf{P}_{15})|} \\ \mathbf{u}_{Pelvis} &= \mathbf{v}_{Pelvis} \times \mathbf{w}_{Pelvis}\end{aligned}\quad (C.11)$$

The position of the right hip joint center ($\mathbf{P}_{HJC,r}$) and left hip joint center ($\mathbf{P}_{HJC,l}$) can be obtained by

$$\mathbf{P}_{HJC,r} = \mathbf{P}_{15} + 0.598A_2\mathbf{u}_{Pelvis} - 0.344A_2\mathbf{v}_{Pelvis} - 0.290A_2\mathbf{w}_{Pelvis} \quad (C.12)$$

$$\mathbf{P}_{HJC,l} = \mathbf{P}_{15} + 0.598A_2\mathbf{u}_{Pelvis} + 0.344A_2\mathbf{v}_{Pelvis} - 0.290A_2\mathbf{w}_{Pelvis} \quad (C.13)$$

With the joint center positions and external marker positions, the segment reference frames (xyz) embedded to the center of gravity of each segment can be generated.

Pelvic segment:

$$\begin{aligned}\mathbf{i}_{Pelvis} &= \mathbf{w}_{Pelvis} \\ \mathbf{j}_{Pelvis} &= \mathbf{u}_{Pelvis} \\ \mathbf{k}_{Pelvis} &= \mathbf{v}_{Pelvis}\end{aligned}\quad (C.14)$$

Right thigh segment

$$\begin{aligned}\mathbf{i}_{Thigh,r} &= \frac{(\mathbf{P}_{HJC,r} - \mathbf{P}_{Knee,r})}{|\mathbf{P}_{HJC,r} - \mathbf{P}_{Knee,r}|} \\ \mathbf{j}_{Thigh,r} &= \frac{(\mathbf{P}_6 - \mathbf{P}_{HJC,r}) \times (\mathbf{P}_{Knee,r} - \mathbf{P}_{HJC,r})}{|(\mathbf{P}_6 - \mathbf{P}_{HJC,r}) \times (\mathbf{P}_{Knee,r} - \mathbf{P}_{HJC,r})|} \\ \mathbf{k}_{Thigh,r} &= \mathbf{i}_{Thigh,r} \times \mathbf{j}_{Thigh,r}\end{aligned}\quad (C.15)$$

Left thigh segment

$$\begin{aligned}\mathbf{i}_{Thigh,l} &= \frac{(\mathbf{P}_{HJC,l} - \mathbf{P}_{Knee,l})}{|\mathbf{P}_{HJC,l} - \mathbf{P}_{Knee,l}|} \\ \mathbf{j}_{Thigh,l} &= \frac{(\mathbf{P}_{Knee,l} - \mathbf{P}_{HJC,l}) \times (\mathbf{P}_{13} - \mathbf{P}_{HJC,l})}{|(\mathbf{P}_{Knee,l} - \mathbf{P}_{HJC,l}) \times (\mathbf{P}_{13} - \mathbf{P}_{HJC,l})|}\end{aligned}\quad (C.16)$$

$$\mathbf{k}_{Thigh,l} = \mathbf{i}_{Thigh,l} \times \mathbf{j}_{Thigh,l}$$

Right calf segment

$$\begin{aligned}\mathbf{i}_{Calf,r} &= \frac{(\mathbf{P}_{Knee,r} - \mathbf{P}_{Ankle,r})}{\left|(\mathbf{P}_{Knee,r} - \mathbf{P}_{Ankle,r})\right|} \\ \mathbf{j}_{Calf,r} &= \frac{(\mathbf{P}_4 - \mathbf{P}_{Knee,r}) \times (\mathbf{P}_{Ankle,r} - \mathbf{P}_{Knee,r})}{\left|(\mathbf{P}_4 - \mathbf{P}_{Knee,r}) \times (\mathbf{P}_{Ankle,r} - \mathbf{P}_{Knee,r})\right|} \\ \mathbf{k}_{Calf,r} &= \mathbf{i}_{Calf,r} \times \mathbf{j}_{Calf,r}\end{aligned}\tag{C.17}$$

Left thigh segment

$$\begin{aligned}\mathbf{i}_{Calf,l} &= \frac{(\mathbf{P}_{Knee,l} - \mathbf{P}_{Ankle,l})}{\left|(\mathbf{P}_{Knee,l} - \mathbf{P}_{Ankle,l})\right|} \\ \mathbf{j}_{Calf,l} &= \frac{(\mathbf{P}_{Ankle,l} - \mathbf{P}_{Knee,l}) \times (\mathbf{P}_{12} - \mathbf{P}_{Knee,l})}{\left|(\mathbf{P}_{Ankle,l} - \mathbf{P}_{Knee,l}) \times (\mathbf{P}_{12} - \mathbf{P}_{Knee,l})\right|} \\ \mathbf{k}_{Calf,l} &= \mathbf{i}_{Calf,l} \times \mathbf{j}_{Calf,l}\end{aligned}\tag{C.18}$$

Right foot segment

$$\begin{aligned}\mathbf{i}_{Foot,r} &= \frac{(\mathbf{P}_2 - \mathbf{P}_{Toe,r})}{\left|(\mathbf{P}_2 - \mathbf{P}_{Toe,r})\right|} \\ \mathbf{k}_{Foot,r} &= \frac{(\mathbf{P}_{Ankle,r} - \mathbf{P}_2) \times (\mathbf{P}_{Toe,r} - \mathbf{P}_2)}{\left|(\mathbf{P}_{Ankle,r} - \mathbf{P}_2) \times (\mathbf{P}_{Toe,r} - \mathbf{P}_2)\right|} \\ \mathbf{j}_{Foot,r} &= \mathbf{k}_{Foot,r} \times \mathbf{i}_{Foot,r}\end{aligned}\tag{C.19}$$

Left foot segment

$$\begin{aligned}\mathbf{i}_{Foot,l} &= \frac{(\mathbf{P}_9 - \mathbf{P}_{Toe,l})}{\left|(\mathbf{P}_9 - \mathbf{P}_{Toe,l})\right|} \\ \mathbf{j}_{Foot,l} &= \frac{(\mathbf{P}_{Ankle,l} - \mathbf{P}_9) \times (\mathbf{P}_{Toe,l} - \mathbf{P}_9)}{\left|(\mathbf{P}_{Ankle,l} - \mathbf{P}_9) \times (\mathbf{P}_{Toe,l} - \mathbf{P}_9)\right|} \\ \mathbf{k}_{Foot,l} &= \mathbf{i}_{Foot,l} \times \mathbf{j}_{Foot,l}\end{aligned}\tag{C.20}$$

The angular kinematics of lower limb during walking can be calculated with the segment reference frames. The following conventions are applicable to all six joints:

$\mathbf{i}_{Distal}$: internal/external rotation axis

$\mathbf{k}_{Proximal}$: flexion/extension axis

$\mathbf{l}_{Joint}$: abduction/adduction axis

$$\mathbf{l}_{Joint} = \frac{\mathbf{k}_{Proximal} \times \mathbf{i}_{Distal}}{|\mathbf{k}_{Proximal} \times \mathbf{i}_{Distal}|} \quad (C.21)$$

α = flexion/extension angle

β = abduction/adduction angle

γ = internal/external rotation angle

Right Hip

$$\alpha_{Hip,r} = \sin^{-1} [\mathbf{l}_{Hip,r} \cdot \mathbf{i}_{Pelvis}] \quad (C.22)$$

$$\beta_{Hip,r} = \sin^{-1} [\mathbf{k}_{Pelvis} \cdot \mathbf{i}_{Thigh,r}] \quad (C.23)$$

$$\gamma_{Hip,r} = -\sin^{-1} [\mathbf{l}_{Hip,r} \cdot \mathbf{k}_{Thigh,r}] \quad (C.24)$$

Left Hip

$$\alpha_{Hip,l} = \sin^{-1} [\mathbf{l}_{Hip,l} \cdot \mathbf{i}_{Pelvis}] \quad (C.25)$$

$$\beta_{Hip,l} = -\sin^{-1} [\mathbf{k}_{Pelvis} \cdot \mathbf{i}_{Thigh,l}] \quad (C.26)$$

$$\gamma_{Hip,l} = \sin^{-1} [\mathbf{l}_{Hip,l} \cdot \mathbf{k}_{Thigh,l}] \quad (C.27)$$

Right Knee

$$\alpha_{Knee,r} = -\sin^{-1} [\mathbf{l}_{Knee,r} \cdot \mathbf{i}_{Thigh,r}] \quad (C.28)$$

$$\beta_{Knee,r} = \sin^{-1} [\mathbf{k}_{Thigh,r} \cdot \mathbf{i}_{Calf,r}] \quad (C.29)$$

$$\gamma_{Knee,r} = -\sin^{-1} [\mathbf{l}_{Knee,r} \cdot \mathbf{k}_{Calf,r}] \quad (C.30)$$

Left Knee

$$\alpha_{Knee,l} = -\sin^{-1} [\mathbf{l}_{Knee,l} \cdot \mathbf{i}_{Thigh,l}] \quad (C.31)$$

$$\beta_{Knee,l} = -\sin^{-1} [\mathbf{k}_{Thigh,l} \cdot \mathbf{i}_{Calf,l}] \quad (C.32)$$

$$\gamma_{Knee,l} = \sin^{-1} [\mathbf{l}_{Knee,l} \cdot \mathbf{k}_{Calf,l}] \quad (C.33)$$

Right Ankle

$$\alpha_{Ankle,r} = \sin^{-1} [\mathbf{l}_{Ankle,r} \times \mathbf{i}_{Calf,r}] \quad (C.34)$$

$$\beta_{Ankle,r} = \sin^{-1} [\mathbf{k}_{Calf,r} \times \mathbf{i}_{Foot,r}] \quad (C.35)$$

$$\gamma_{Ankle,r} = -\sin^{-1} [\mathbf{l}_{Ankle,r} \cdot \mathbf{k}_{Foot,r}] \quad (C.36)$$

Left Ankle

$$\alpha_{Ankle,l} = \sin^{-1} \left[\mathbf{l}_{Ankle,l} \cdot \mathbf{i}_{Calf,l} \right] \quad (\text{C.37})$$

$$\beta_{Ankle,l} = -\sin^{-1} \left[\mathbf{k}_{Calf,l} \cdot \mathbf{i}_{Foot,l} \right] \quad (\text{C.38})$$

$$\gamma_{Ankle,l} = \sin^{-1} \left[\mathbf{l}_{Ankle,l} \cdot \mathbf{k}_{Foot,l} \right] \quad (\text{C.39})$$

Appendix-D

Adjusted Lower Limb Joints Angle

Figure D-1: Adjusted Lower Limb Joints Angle of Subject 1

Figure D-2: Adjusted Walking Motions of Subject 1 (Red Triangle Representing the Foot, Graph Unit is mm)

Figure D-3: Adjusted Lower Limb Joints Angle of Subject 2

Figure D-4: Adjusted Walking Motions of Subject 2 (Red Triangle Representing the Foot, Graph Unit is mm)

Figure D-5: Adjusted Lower Limb Joints Angle of Subject 3

Figure D-6: Adjusted Walking Motions of Subject 3 (Red Triangle Representing the Foot, Graph Unit is mm)

Figure D-7: Adjusted Lower Limb Joints Angle of Subject 4

Figure D-8: Adjusted Walking Motions of Subject 4 (Red Triangle Representing the Foot, Graph Unit is mm)

Figure D-9: Adjusted Lower Limb Joints Angle of Subject 5

Figure D-10: Adjusted Walking Motions of Subject 5 (Red Triangle Representing the Foot, Graph Unit is mm)

Figure D-11: Adjusted Lower Limb Joints Angle of CGA Data

Figure D-12: Adjusted Walking Motions of CGA Data (Red Triangle Representing the Foot, Graph Unit is mm)

Appendix-E

List of Publications

Journal papers

1. Trieu Phat Luu, K. H. Low, Xingda Qu, H. B. Lim and K. H. Hoon. “An individual-specific gait pattern prediction model based on generalized regression neural networks,” *Gait & Posture*, vol. 39, pp. 443-448, 2014.
2. Trieu Phat Luu, K. H. Low, Xingda Qu, H. B. Lim and K. H. Hoon. “Hardware Development and Locomotion Control Strategy for an Over-ground Gait Trainer: *NaTure-gaits*,” *IEEE Translational Engineering in Health and Medicine*, vol. 2, pp. 1-9, 2014.

Conference papers

1. Trieu Phat Luu, K. H. Low, and Xingda Qu. “An individual-specific pelvic motion prediction model for robotic gait rehabilitation systems”. Accepted for *IEEE International Conference on Robotics and Biomimetics (ROBIO 2012)*, Guangzhou, China, Dec 2012.
2. Trieu Phat Luu, K. H. Low, Xingda Qu, H. B. Lim and K. H. Hoon. “Study impact of Robotic Gait Rehabilitation System on Ground Reaction Force and Center of Pressure”. Accepted for *IEEE Healthcare Technology Conference: Translational Engineering in Health & Medicine (HIC 2012)*, Houston, TX, Nov 2012.
3. Trieu Phat Luu, K. H. Low, Xingda Qu, H. B. Lim and K. H. Hoon. “On the development of an over-ground gait rehabilitation system: *NaTure-gaits*. Accepted for *IEEE Healthcare Technology Conference: Translational Engineering in Health & Medicine (HIC 2012)*, Houston, TX, Nov 2012.
4. Luu TP, Lim HB, Hoon KH, Qu X, Low KH, editors. “Subject-specific gait parameters prediction for robotic gait rehabilitation via generalized regression neural network”, in *proceeding of the IEEE International Conference on Robotics and Biomimetics (ROBIO 2011)*, Phuket, Thailand, Dec. 2011.

5. Lim HB, Luu TP, Hoon KH, Qu X, Tow A, Low KH. "Study of body weight shifting on robotic assisted gait rehabilitation with *NaTure-gaits*", in *proceeding of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2011), San Francisco, California, Sept. 2011*.
6. Trieu Phat Luu, H.B. Lim, Xingda Qu, K. H. Hoon and K. H. Low, "Subject Specific Lower Lim Waveforms Planning via Artificial Neural Network", in *proceeding of IEEE 11th International Conference on Rehabilitation Robotics (ICORR2011), Zurich, Switzerland, Jul 2011*.
7. Trieu Phat Luu, H. B. Lim, Xingda Qu, and K. H. Low , "Natural Pelvic Motion Assistance with Adaptive Body Weight Support for *NaTure-gaits*", in *proceeding of the 8th Asian Control Conference (ASCC2011), Taiwan, May 2011*
8. Trieu Phat Luu, H. B. Lim, Xingda Qu, and K. H. Low, "Subject Tailored Gait Pattern Planning for Robotic Gait Rehabilitation," in *Proceedings of the International Conference on Robotics and Biomimetics (ROBIO2010), Tianjin, China, Dec 2010*.
9. H. B. Lim, Trieu Phat Luu, K. H. Hoon, and K. H. Low, "Natural Gait Parameters Prediction for Gait Rehabilitation via Artificial Neural Network," in *proceeding of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2010), Taipei, Taiwan, 2010*.
10. H. B. Lim, Trieu Phat Luu, K. H. Hoon, Xingda Qu, and K. H. Low, "Body Weight Support with Natural Pelvic Motion Assistance for Robotic Gait Rehabilitation," in *proceeding of International Conference on Advanced Mechatronics 2010, OSAKA, JAPAN, 2010*.