ABSTRACT

WANG, DING. Design of An Expert System to Automatically Tune the Impedance Control for Powered Knee Prostheses. (Under the direction of He Huang, Gregory S. Sawicki, and Nagle H. Troy).

Compared to passive devices, powered above-knee prostheses can help transfemoral amputee subjects regain natural locomotion. Currently, most powered prostheses use finite state impedance control for which the controller parameters are typically fine-tuned by a human expert, which is time and resource intensive. Therefore, approaches to automate and shorten the tuning procedure would greatly improve the setup and tuning process. In this work, an automated fuzzy rule-based tuning system was built to replace the human expert. We first studied the relationship between impedance control parameters and prosthetic knee measurements. Then tuning rules were established from data collected while a human expert tuned the prosthesis control parameters. The auto-tuning system was tested on two able-bodied subjects and one transfemoral amputee. Auto-tuned impedance parameters generated powered prosthesis knee angles that closely matched knee angles of able-bodied subjects during gait. However, the auto-tuned gait symmetry, step width, and trunk movement were not as good as those observed following expert tuning. This implies that tuning impedance control parameters to track a desired prosthesis knee angle profile might not guarantee an improvement in gait performance. Future studies are needed to determine the additional parameters related to gait performance that should be monitored while tuning the impedance control parameters.
Design of An Expert System to Automatically Tune the Impedance Control for Powered Knee Prostheses

by
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INTRODUCTION

It’s estimated that in 2005, a total of 1,027,000 people lived with lower limb loss, and over half of them are with major amputation [1]. Amputations in the United States are expected to increase by 58,000 per year by 2030 [2]. By 2050, the number of person living with the loss of a limb is expected to more than double from 2005. Therefore, there is a pressing need to restore the locomotion function of the increasing number of lower limb amputees.

Recently developed modern powered knee prostheses could help transfemoral (TF) amputees regain natural locomotion [3-7]. Most of these experimental systems rely on finite state impedance control, which adjusts the impedance of knee joints based on gait states. For example, in [8], researches divided the gait cycle into 5 states, and for each state there were 3 impedance parameters. The form of the impedance controller for each state is shown in equation (1), where $k$, $\theta_E$ and $C$ denoted the linear stiffness, equilibrium position, and damping coefficient, respectively; $\theta_p$ and $\dot{\theta}_p$ represented measured knee joint angle and angular velocity, respectively; $\tau$ was the joint torque. To control the powered knee prosthesis, they determined the values of 15 impedance parameters in total.

$$\tau = k(\theta_p - \theta_E) + C\dot{\theta}_p$$  (1)

To ensure high performance of the controller, parameters of the controller, especially the desired impedance in each gait phase, had to be fine-tuned for each subject to generate a natural walking gait pattern due to inter-subject variation. Currently the related tuning procedures are performed by a human expert, usually through trial and error and conducted based on gait analysis and patients feedback [6]. Our previous experience indicates that the
time to complete the parameter tuning procedures is about 10 to 20 minutes even under the direction of experienced experimenters. Any effort to automate and shorten the tuning procedures will have positive clinical impacts.

Three approaches have been explored to shorten the impedance calibration procedure for lower limb prostheses: (1) improving experimenters’ skill through training, (2) decreasing the number of parameters needed for tuning, and (3) developing automatic calibration approaches. Most of leading manufactures use the first approach and develop their own training programs and graphic user interfaces (GUIs) to help prosthetists tune prostheses control parameters for individual patients. Although the training programs for prosthetists and patients work well when the number of adjustable parameters is limited, they are not expected to be efficient solutions if the number of adjustable parameters increases, for example, when tuning the prostheses to negotiate different terrains.

For the second approach, the commonly used method to reduce the number of tuning parameters is modeling. The basic idea is to use measurable or known parameters to estimate some of the unknown impedance values through biomechanical models. However, the success of using biomechanical modeling to simplify the calibration procedure has been limited. For example, Eilenberg and Herr [9] proposed control logic based on a neuromuscular model and successfully reduced the number of tuning parameters for an ankle-foot prosthesis. Currently, this patented technology is only applied on transtibial prostheses. Actually, modeling human lower limb joint impedance during dynamic movements, such as walking, is inevitably difficult. This is because human joint impedance varies with angular position [10, 11], neural
activation [12], and externally applied torque [13]. In addition, an amputee-prosthesis integrated multibody system is very complex. Furthermore, measuring human joint impedance in dynamic movements, such as walking on uneven terrain, is experimentally difficult and expensive, which makes the validation of joint dynamic models challenging.

Some previous studies have estimated joint impedance values. In [10, 11], they estimated the passive and active stiffness of the ankle joint and defined it as a function of joint angle and time. During their experiment, subjects were highly controlled and their joints were constrained in certain positions, which differed from the joint behavior during locomotion. A muscle activation based modeling approach was introduced in [14, 15]. Knee joint stiffness could be estimated using a musculoskeletal model of the leg with EMG without applying perturbations. But the approach was only validated for isometric conditions. Some studies [16-19] used the concept of quasi-stiffness to characterize the stiffness of lower-limb joints. The quasi-stiffness value was estimated as the slope of the best linear fit on the moment-joint plot during different locomotion tasks, such as walking ([19]), running ([18]) and stepping down ([17]), or different speeds ([19]). The quasi-stiffness and stiffness were equivalent in the context of passive joints, but different in the context of powered joints [20]. In [21-23], they developed a set of general models of joint stiffness during the stance phase of walking and used experimental walking data to obtain best-fit linear regressions. The final simplified model with only subject height and weight could estimate the quasi-stiffness for preferred walking speed. However, the estimation was limited to stance phase. The third reported approach is to tune the prosthesis control parameters using online learning or rules. Blaya and
Herr realized automated parameter tuning for an active ankle-foot orthosis [24]. Impedance parameters in two gait phases were adjusted to maintain a constant frequency of slaps and avoid orthosis oscillation. Although foot drops were avoided, the event (slap and oscillation)-driven calibration rules had to rely on predefined events, which can only be triggered or avoided if the impedance parameters were at their targeted values. An auto-tuning system helped a semi-active knee prosthesis gain the capacity to adapt to different walking speeds [25]. Success of this system on tuning the joint damping ratio relied on a linear relationship between damping and walking speed. This type of relationship is hard to establish and validate when more than one adjustable impedance values exists. Recently, in [26], they developed modified intrinsic control strategies to mimic the behavior of knee and ankle joints for different ambulation modes. The number of parameters that needed to be independently adjusted was decreased and the accommodation period for the users was shortened.

Despite the success of these approaches, research effort for developing automated impedance calibration system has been limited for powered knee prostheses. This was partly due to the lack of knowledge about the precise relationship between the impedance parameters and certain measurements from powered knee prostheses.

Currently we do not fully understand the whole system and the relationships between gait measurements and impedance control parameters are not well defined. But there is already a controller in place to effectively tune the impedance parameters: a human expert. Therefore, we can study how the expert tuned the impedance parameters and build a system to mimic the expert.
The goal of this study was to present an automated computer-based tuning system to replace the human expert and automatically tune the knee impedance parameters for finite state impedance control of powered knee prostheses. There have usually been two types of automated tuning systems: rule-based systems and case-based reasoning systems. Rule-based system contains information obtained from a human expert, and represented that information in the form of rules. Case-based reasoning adapts solutions of previous problems and uses them to solve new problems; it is necessary to build a case-base to store previous problems and solutions. We expect that the human expert is more likely to follow certain rules in his mind to change the impedance parameters. Therefore, here we chose the rule-based system. Fuzzy logic inference was selected because it had the advantages of emulating the behavior of the experienced expert (e.g. experimenters or prosthetists) and of dealing with the uncertainty in the system. In addition, the fuzzy logic system avoids the requirements of previous clinical knowledge to formulate the relationship between the inputs and outputs.

The structure of the fuzzy controller, shown in Figure 1, consisted of fuzzification, fuzzy rule-base, inference engine, and defuzzification blocks. In the fuzzification block, the inputs were divided into different fuzzy regions (membership functions) so that they could be interpreted and compared to the rules in the rule-base. The rule-base stored the knowledge, in the form of a set of “IF… THEN…” rules, of how to control the system. The inference engine evaluated which control rules were used based on the inputs and then decided what the output should be. The defuzzification block converted the conclusions of the inference engine into numerical output.
During the expert tuning procedure, the impedance parameters were tuned based on the expert’s observation and clinic gait analysis, which might include knee joint angles and gait phase duration. To develop the fuzzy tuner, it is necessary to determine which gait-related parameters should be monitored to change each individual impedance parameter.

After determining the inputs and outputs of the rules, the rule-base for the fuzzy controller can be built. Input-output data pairs collected during the expert tuning procedure are used to generate fuzzy rules [27]. As an example, suppose we collect a set of desired input-output data pairs:

\[ (x_1^{(1)}, x_2^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}; y^{(2)}), \ldots \]  

(2)

where \( x_1 \) and \( x_2 \) are inputs, and \( y \) is the output. Fuzzy rules can be generated from them to determine the mapping \( f: (x_1, x_2) \rightarrow y \). This mapping procedure can be divided into 4 steps.
For step 1, the input and output spaces were divided into several fuzzy regions distinguished by a set of fuzzy membership functions (MF). Assume the domain intervals of \( x_1, x_2, \) and \( y \) are \([x_1^-, x_1^+], [x_2^-, x_2^+], \) and \([y^-, y^+]\), respectively. The variable will most probably lie into its domain interval, but still can lie outside this interval. Each domain interval was divided into \( N \) regions and assigned a fuzzy membership function. As shown in Figure 2, for the input \( x_1^{(1)} \), there are five MFs: S2 (small 2), S1 (small 1), CE (center), B1 (big 1), and B2 (big 2). The shape of each MF is triangular.

For step 2, fuzzy rules will be generated from the data pairs. First, the degree of given \( x_1^{(1)}, x_2^{(1)}, \) and \( y^{(1)} \) in each MF are determined. For example, as shown in Figure 2, \( x_1^{(1)} \) has degree 0.8 in MF B1, degree 0.2 in MF B2, and 0 degrees in all other MFs. Second, assign a given \( x_1^{(i)}, x_2^{(i)}, \) or \( y^{(i)} \) to the MF with the highest degree. In the example, \( x_1^{(1)} \) is considered to be B1, and \( x_1^{(2)} \) is considered to be B1. The same procedure was applied to each input and output variable.
Finally, obtain one rule from one pair of desired input-output data, e.g.,

\[
(x_1^{(1)}, x_2^{(1)}; y^{(1)}) \Rightarrow [x_1^{(1)}(0.8 \text{ in } B_1, \text{max}), x_2^{(1)}(0.7 \text{ in } S_1, \text{max}); y^{(1)}(0.9 \text{ in } CE, \text{max})] \Rightarrow \\
\text{Rule 1: IF } x_1 \text{ is } B_1 \text{ and } x_2 \text{ is } S_1, \text{ THEN } y \text{ is } CE.
\]

\[
(x_1^{(2)}, x_2^{(2)}; y^{(2)}) \Rightarrow [x_1^{(2)}(0.6 \text{ in } B_1, \text{max}), x_2^{(2)}(1 \text{ in } CE, \text{max}); y^{(2)}(0.7 \text{ in } B_1, \text{max})] \Rightarrow \\
\text{Rule 2: IF } x_1 \text{ is } B_1 \text{ and } x_2 \text{ is } CE, \text{ THEN } y \text{ is } B_1.
\]

For step 3, a degree is assigned to each rule. Since each data pair generates one rule, it is probable that there will be some conflicting rules. These rules have the same IF part but different THEN parts. To resolve the conflict, a degree will be assigned for each rule, and only the rule with maximum degree in the conflict group will be accepted.

The degree of each rule is calculated as the product of the degrees of all the inputs and outputs. For the rule: “IF \( x_1 \) is A and \( x_2 \) is B, THEN \( y \) is C.” its degree, denoted by \( D(\text{Rule}) \), is
\[ D(Rule) = m_A(x_1)m_B(x_2)m_C(y) \]  \hspace{1cm} (3)

Rule 1 has degree
\[ D(Rule\,1) = m_{B_1}(x_1)m_{S_1}(x_2)m_{CE}(y) = 0.8 \times 0.7 \times 0.9 = 0.504 \]  \hspace{1cm} (4)

And Rule 2 has degree
\[ D(Rule\,2) = m_{B_1}(x_1)m_{CE}(x_2)m_{B_1}(y) = 0.6 \times 1 \times 0.7 = 0.42 \]  \hspace{1cm} (5)

For step 4, we will build the combined fuzzy rule base. The combined fuzzy rule base is assigned the rules chosen for each input MF pair.

In order to build the auto-tuning system, the whole study was divided into three aims. The purpose of aim one was to determine the desired inputs and outputs of the auto-tuning system. Aim two determined the fuzzy rules based on human expert tuning and subsequent changes in gait parameters. After building up the rule base and auto-tuning controller, the whole system was built and tested in aim three. The tuning performance of the auto-tuning system was evaluated and compared with expert tuning procedure. The results of this study might pave a new way for efficient impedance tuning for powered knee prostheses and advance the practical value of powered knee prosthesis for daily use.
AIM ONE: DETERMINE THE PARAMETERS USED FOR THE TUNING OF IMPEDANCE PARAMETERS

Introduction

Currently, most powered prostheses use an intrinsic controller consisting of a finite state machine and impedance controller. To mimic the periodic walking motion, each gait cycle is partitioned into multiple states using finite state machine. For each state, based on the impedance control proposed in [28-30], the biological knee impedance can be matched by a prosthesis mimicking a passive spring-damper-system with predefined impedance parameters (i.e. stiffness, equilibrium position, and damping). The desired joint torque generated by the powered prosthesis in each state is calculated based on its impedance parameters.

Traditionally, an experienced experimenter was needed to find the appropriate impedance parameter values. As described in [31], during the manual tuning procedure, the impedance parameters were iteratively adjusted by the expert according to the joint sensor data, video recordings and user feedback. For example, if the joint was not generating enough torque during support, the stiffness would be increased or the stiffness set point altered. The impedance parameter values are tuned with this iterative process, which is challenging for the expert and time consuming. Since an expert needs to be involved during the tuning procedure, it is costly especially on a commercial scale.

Recently, auto-tuning systems have been built to replace the expert and tune the parameters for orthoses and prostheses. In [24], an event-driven rule-based system was built to tune the parameters for the control of an active ankle-foot orthosis. An auto-tuning system,
which relied on a linear relationship between damping and walking speed, helped a semi-active knee prosthesis gain the capacity to adapt to different walking speeds [6]. Despite the success of these approaches in orthoses and prostheses, research efforts for developing automated impedance calibration systems has been limited for powered knee prostheses. This is partly due to the lack of a precise relationship between the impedance parameters and certain measurements from the powered knee prosthesis.

Instead of figuring out the precise relationship between the impedance parameters and prosthesis measurements, we determined that we could directly learn from the expert’s tuning procedure to build an auto-tuning system. To build this system, we first needed to determine which signals from the powered knee prosthesis were to be selected as the tuning inputs. In this chapter, we discuss how we developed the relationships between the prosthetic sensor feedback signals and each impedance parameter. The results of this chapter helped us determine the inputs and outputs of the tuning rules of the auto-tuning system.

**Material and Methods**

**Experimental setup**

In our group, we designed a powered knee prosthesis prototype [32]. A moment arm and a pylon were used to construct the knee joint. The joint angle was driven by a DC motor (Maxon, Switzerland) through a ball screw. Sensors on the powered knee prosthesis allowed us to directly measure real-time mechanical feedback. A potentiometer was instrumented on the knee joint to measure the knee joint angle, and an encoder was connected with the motor
to obtain the knee joint angular velocity. A 6 degree of freedom load cell (ATI, NC) was mounted on the pylon to measure the ground reaction force (GRF). The designed powered prosthesis was tethered and controlled by a desktop PC. A multi-functional DAQ card (National Instruments, TX) collected all the sensor measurements at 100Hz. It also provided a D/A for control output to drive the DC motor through a motor controller (Maxon, Switzerland).

The control of the powered knee prosthesis was based on finite-state impedance control. For level ground walking mode, the impedance controller consisted of five states (gait phases): initial double support (IDS), single support (SS), terminal double support (TDS), swing flexion (SWF), and swing extension (SWE). The definitions of the phases were based on the gait phases in [33]. The transitions between the states in finite state machine were triggered by the GRF, knee joint angle, and knee joint angular velocity measured from the prosthesis [8]. In each state, desired prosthesis joint impedances were defined to mimic the knee impedance characteristics in AB subjects. There were three impedance parameters, as shown in (6), for each state. An impedance parameter profile was built to store all 15 impedance parameters. The desired knee joint torques, $\tau$, was calculated based on (6) and generated by the motor.

$$\tau = k(\theta_p - \theta_E) + C\dot{\theta}_p$$  \hspace{2cm} (6)

, where $k$, $\theta_E$ and $C$ were the linear stiffness, equilibrium position, and damping coefficient; $\theta_p$ and $\dot{\theta}_p$ were measured knee joint angle and angular velocity, respectively.
Figure 3. Architecture of the Finite Statement Impedance Control system of powered knee prosthesis [8]

The experiment was conducted on a split belt treadmill that was instrumented with two separate force platforms, one under each belt (BERTEC, Columbus, OH, USA). Force data were recorded during walking trials, using the two force platforms. The sampling frequency was 1000 Hz. Participants were asked to walk with each foot stepping on separate belt of the treadmill.

**Experimental protocol**

This study was approved by Institutional Review Board (IRB) of the University of North Carolina at Chapel Hill and with informed consent of the subjects. Two able-bodied
(AB) subjects and one transfemoral (TF) amputee subject were recruited for this study. A special adaptor was designed for the AB subjects so that they could walk with the powered knee prosthesis. The subjects had received 10 hours of treadmill walking training with the powered knee prosthesis prior to the experiment with appropriate impedance parameter profiles, which were manually tuned by an experienced experimenter.

All the subjects’ walking trials were conducted on a split belt treadmill that was instrumented with two separate force platforms, one under each belt (BERTEC, Columbus, OH, USA). Subjects completed 27 2-min walking trials with different impedance parameter profiles at 0.6 m/s. A 5-min rest was conducted after every 5 walking trials. A harness system was used for protection during the trials. The subjects were instructed to avoid holding the handrails as much as possible.

The impedance parameter profiles were generated by the following method: For each impedance parameter, we set three different levels: a low-level, a middle-level, and a high level. The initial low-level and high-level values of each parameter were set to the minimum and maximum values of each impedance parameter from 4 AB and 1 TF amputee subjects’ existing expert-tuned profiles, respectively. The middle level values for each parameter were defined as the midpoint of the fine-tuned low-level and high-level values. For each gait phase, there were 27 different combinations of the 3 impedance parameters based on their 3 different levels. We randomized the order of 27 combinations for each phase and then built 27 different initial impedance parameter profiles.
Figure 4. 27 initial impedance parameter profiles. Blue dot indicated the position of each initial impedance parameter profile in the 3D impedance space.

Based on the expert’s report and another study [6, 26], usually the prosthetic knee joint angle was used as the target of tuning. The knee joint profile related parameters included peak knee angle [34], gait phase duration [34], and peak angular velocity [35] of different phases. These knee parameters were measured for 10 continuous strides for each trial, and then averaged. Three-way analysis of variance (ANOVA) was used to examine the influence of each impedance parameter on the knee parameters. P-value was chosen as 0.1. If the p-value between a knee parameter and impedance parameter was smaller than 0.1, the knee parameter was deemed to be significantly affected by changes in the corresponding impedance parameter. Therefore, the knee parameter was selected and used to build impedance parameter tuning rules. Then, for each of the selected knee parameters, the influence of the interaction between different impedance parameters was further studied. If the p-value between the knee parameter
and the interaction between multiple impedance parameters was smaller than 0.1, then the interaction of the impedance parameters would be considered when building the tuning rules.

**Results**

Table 1 showed the knee parameters and their related impedance parameters for each gait phase. For all five phases, only peak knee angle, phase duration, and peak angular velocity were selected, and peak knee joint angle was always related with equilibrium position, and phase duration was always related with stiffness. Some of the knee parameters were related with multiple impedance parameters. For example, the maximum swing extension knee joint angle was related with stiffness, equilibrium position, and damping value in that phase. Stiffness was related to all of the knee parameters, except maximum stance extension knee joint angle.
Table 1. Selected knee parameters with related impedance parameters for each phase (p-value < 0.1)

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<th>Phase</th>
<th>Parameter</th>
<th>Impedance Parameter (p-value)</th>
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<td>Initial Double Support</td>
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<td>Terminal Double Support</td>
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<td>Swing Extension</td>
</tr>
<tr>
<td>$\theta_e$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2 showed the influence of interaction between multiple impedance parameters on the selected knee parameters. Since all of the p-values were larger than 0.1, the interaction between multiple impedance parameters would not be considered.

Table 2. Influence of interaction between multiple impedance parameters on the knee parameters

<table>
<thead>
<tr>
<th></th>
<th>IDS</th>
<th>SS</th>
<th>TDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{\text{peak}}$</td>
<td>0.12</td>
<td>0.63</td>
<td>0.84</td>
</tr>
<tr>
<td>$T_{\text{dura}}$</td>
<td>0.15</td>
<td>0.59</td>
<td>0.89</td>
</tr>
<tr>
<td>$\theta_{\text{peak}}$</td>
<td>0.42</td>
<td>0.90</td>
<td>0.79</td>
</tr>
<tr>
<td>$K$*$\theta_e$</td>
<td>0.37</td>
<td>0.78</td>
<td>0.82</td>
</tr>
<tr>
<td>$\theta_e$*C</td>
<td>0.46</td>
<td>0.13</td>
<td>0.42</td>
</tr>
<tr>
<td>$C$*K</td>
<td>0.66</td>
<td>0.26</td>
<td>0.94</td>
</tr>
<tr>
<td>$K$*$\theta_e$*C</td>
<td>0.77</td>
<td>0.98</td>
<td>0.61</td>
</tr>
</tbody>
</table>
Table 2. Continued

<table>
<thead>
<tr>
<th></th>
<th>SWF</th>
<th></th>
<th>SWE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>K*θ_E</td>
<td>θ_peak 0.49</td>
<td>T_dura 0.58</td>
<td>θ_peak 0.97</td>
<td>T_dura 0.25</td>
</tr>
<tr>
<td>θ_E*C</td>
<td>θ_peak 0.18</td>
<td>T_dura 0.42</td>
<td>θPeak 0.98</td>
<td>T_dura 0.60</td>
</tr>
<tr>
<td>C*K</td>
<td>θ_peak 0.63</td>
<td>T_dura 0.48</td>
<td>θPeak 0.76</td>
<td>T_dura 0.79</td>
</tr>
<tr>
<td>K<em>θ_E</em>C</td>
<td>θ_peak 0.19</td>
<td>T_dura 0.21</td>
<td>θPeak 0.93</td>
<td>T_dura 0.94</td>
</tr>
</tbody>
</table>

Discussion

The differences in gait performance while using the powered knee prosthesis were related with the differences in the impedance parameters. However, the relationships were not clear. In this step, we tried to figure out the relationships and use them to build the auto-tuning system. The results showed that there were not only one-to-one relationships between the knee parameters and impedance parameters. In some phases, impedance parameters were related with multiple knee parameters, which meant during tuning, the adjustment of the impedance parameters should be determined by multiple knee parameters. For example, the swing extension stiffness was related with maximum swing extension knee joint angle, swing extension phase duration, and maximum swing extension angular velocity. If we tried to adjust the swing extension stiffness, all three knee parameters needed to be considered. Results in Table 2 showed that there were no strong relationships between the knee parameters and interactions of the impedance parameters. This meant that the effects of different impedance parameters on each knee parameter could be considered as independent from each other. In general, the rules for impedance parameter tuning were multiple-input (one or multiple knee parameters) - one-output (one impedance parameter) rules.
Conclusion

In this step, we figured out which knee parameters had strong relationships with each impedance parameter in each gait phase. Peak knee joint angles, phase duration, and peak knee joint angular velocity were selected. The multiple-to-one relationship between the knee parameters and impedance parameters indicated that the impedance parameter value should be determined by multiple knee parameters, and no interaction between impedance parameters needed to be considered. These relationships would lead us to build the auto-tuning controller for the system.
AIM TWO: GENERATE FUZZY RULE BASES FOR FUZZY CONTROLLERS

Introduction

Despite the success of the auto-tuning approaches introduced in orthoses and prosthesis [24, 25], research effort for developing automated impedance tuning system had been limited for powered knee prosthesis. The difficult in building an auto-tuning system was that we didn’t fully understand the whole human-prosthesis system, and the relationships between the gait and impedance parameters were not well defined. One of the solutions was directly learning from the existing controller that we already had: the human expert. Auto-tuning expert system could be built to mimic the human expert tuning procedure. There were usually two types of expert system: rule-based system and case-based reasoning. In our case, when expert did the tuning, he was more likely to follow the rules in his mind. Therefore, we chose the rule-based expert system. Fuzzy logic inference was selected because it has the advantages of emulating the behavior of the experienced expert (e.g. experimenters or prosthetists) and of dealing with the uncertainty in the system. In addition, the fuzzy logic system avoids the requirements of previous clinical knowledge to formulate the precise relationship between the inputs and outputs.

In previous chapter, we had determined which measurements from powered knee prosthesis were used for the tuning of each impedance parameter. These measurements were the inputs of the fuzzy controller, and their corresponding impedance parameters were the output of the fuzzy controller. In this chapter, we discussed how to generate the fuzzy tuning
rules by learning from the expert tuning procedure. Based on the rules, we built the fuzzy controller and the auto-tuning system.

**Material and Method**

**Architecture of the Auto-tuning System**

Figure 5 showed the architecture of the powered knee prosthesis control with auto-tuning system. The Buffer block in the system stored the data collected from powered knee prosthesis, including knee joint angle ($\theta$), angular velocity ($\dot{\theta}$), and GRF. Then these data were sent to Feature block. In the Feature block, the knee parameters ($\theta_{peak}$, $T_{dura}$, and $\dot{\theta}_{peak}$) in each gait phase were calculated and averaged from multiple strides. The knee parameters ($\theta^T_{peak}$, $T^T_{dura}$, and $\dot{\theta}^T_{peak}$) obtained from the walking knee profile of AB were used as the target. The errors ($\Delta\theta^T_{peak}$, $\Delta T^T_{dura}$, and $\Delta\dot{\theta}^T_{peak}$) between the target and the parameters obtained from Feature block were the inputs of the Fuzzy Auto-tuning Controller block. The outputs of the controller ($\Delta k$, $\Delta\theta_E$, and $\Delta C$) were the adjustments of impedance parameters in each gait phase. The auto-tuning controller would update the impedance parameters stored in Finite State Machine.
Figure 5. The architecture of powered knee prosthesis control with auto-tuning system.

In the Auto-tuning Controller block, there were five fuzzy controllers for the five different gait phases. Figure 6 showed the structure of the fuzzy controller for swing extension phase as an example. Inputs of the fuzzy controller were the error of peak swing extension angle ($\Delta \theta^T_{peak}$), error of swing extension phase duration ($\Delta T^T_{dura}$), and error of peak swing extension angular velocity ($\Delta \dot{\theta}^T_{peak}$). In fuzzification part, the inputs were normalized based on their maximum absolute values during the expert tuning procedure. Two membership functions (N: negative, P: positive) were used as shown in the figure and each input was fuzzified as N
and P with their degrees. Three rule bases were built for the three impedance parameters. The fuzzified inputs were sent to each rule base according to the result in aim one. For example, the change of stiffness was related to peak knee angle, phase duration, and peak angular velocity (Table 1), therefore all three fuzzified inputs were sent to the rule base for the tuning of stiffness; the rules for the change of equilibrium position was only related to peak knee angle and phase duration, therefore only the error of peak knee joint angle and phase duration were sent to this rule base.

The fuzzification and defuzzification methods were discussed later in this part. The outputs of the fuzzy control, which were the adjustment of impedance parameter ($\Delta k$, $\Delta \theta_E$, and $\Delta C$), equaled to the normalized defuzzification output multiplied by its gain, which was the maximum change for each impedance parameter during expert tuning procedure.
Figure 6. Structure of the fuzzy controller for swing extension phase in the Auto-Tuning block

The general method to generate fuzzy rules from numerical data based was discussed in the INTRODUCTION part. Here we discussed how to get the fuzzy rules for the fuzzy controller in our auto-tuning system. Suppose we collected a set of desired input-output data pairs for the tuning of equilibrium position in swing extension phase:

\[
\left( x_1^{(1)}, x_2^{(1)}, y^{(1)} \right), \left( x_1^{(2)}, x_2^{(2)}, y^{(2)} \right), \ldots
\]  

where \( x_1 \) and \( x_2 \) were error of peak knee joint angle \( \Delta \theta_{\text{peak}} \) and phase duration \( \Delta T_{\text{dura}} \), respectively; and \( y \) is the change of equilibrium position \( \Delta \theta_E \). Fuzzy rules can be generated from them to determine the mapping \( f: (\Delta \theta_{\text{peak}}, \Delta T_{\text{dura}}) \rightarrow \Delta \theta_E \).
For step 1, we divided the input and output spaces into fuzzy regions. The inputs and output were normalized based on its maximum absolute value during the expert tuning procedure. To simplify the calculation, each domain interval was divided into 2 regions and each region was assigned a fuzzy membership function (MF). As shown in Figure 7, for the input $x_1^{(1)}$, there were N (negative) and P (positive). The shape of each MF is triangular.

For step 2, fuzzy rules were generated from the data pairs. First, the degree of given $x_1^{(1)}$, $x_2^{(1)}$, and $y^{(1)}$ in each MF were determined. For example, $x_1^{(1)}$ had degree 0.8 in MF N, degree 0.2 in MF P; $x_2^{(1)}$ had degree 0.4 in MF N, degree 0.6 in MF P. Second, assigned a given $x_1^{(i)}$, $x_2^{(i)}$, or $y^{(i)}$ to the MF with maximum degree. So, $x_1^{(1)}$ was considered to be N, and $x_1^{(2)}$ was considered to be P.
Figure 7. Divisions of the inputs $x_1^{(i)}$ and $x_2^{(i)}$, and output $y^{(i)}$ spaces into fuzzy regions and corresponding membership functions.
Finally, obtained one rule from one pair of desired input-output data, e.g.,

\[
(x^{(1)}_1, x^{(1)}_2, y^{(1)}) \Rightarrow [x^{(1)}_1 (0.8 \text{ in } N, \text{max}), x^{(1)}_2 (0.9 \text{ in } N, \text{max}); y^{(1)} (0.7 \text{ in } P, \text{max})] \Rightarrow 
\]

**Rule 1:** IF $\Delta \theta_{peak}$ is N and $\Delta T\_dura$ is N, THEN $\Delta \theta_E$ is P.

\[
(x^{(2)}_1, x^{(2)}_2, y^{(2)}) \Rightarrow [x^{(2)}_1 (0.6 \text{ in } P, \text{max}), x^{(2)}_2 (0.6 \text{ in } P, \text{max}); y^{(2)} (0.9 \text{ in } N, \text{max})] \Rightarrow 
\]

**Rule 2:** IF $\Delta \theta_{peak}$ is P and $x_2$ is $\Delta T\_dura$, THEN $\Delta \theta_E$ is N.

For step 3, a degree was assigned to each rule. Since each data pair generated one rule, it was probable that there would be some conflicting rules, which had same IF part but different THEN parts. To resolve the conflict, a degree was assigned for each rule, and only the rule with maximum degree in the conflict group was be accepted.

The degree of each rule was defined as the product of the degrees of all the inputs and outputs. For the rule: “IF $x_1$ is A and $x_2$ is B, THEN y is C.” its degree, denoted by $D(\text{Rule})$, is

\[
D(\text{Rule}) = m_A(x_1)m_B(x_2)m_C(y) 
\]  

(8)

As examples, Rule 1 has degree

\[
D(\text{Rule1}) = m_{B1}(x_1)m_{S1}(x_2)m_{CE}(y) = 0.8 \times 0.9 \times 0.7 = 0.504
\]  

(9)

And Rule 2 has degree

\[
D(\text{Rule2}) = m_{B1}(x_1)m_{CE}(x_2)m_{B1}(y) = 0.6 \times 0.6 \times 0.9 = 0.324
\]  

(10)

For step 4, we built the combined fuzzy rule base. The combined fuzzy rule base was assigned rules from the rules generated from numerical data as shown in Figure 8. If there was more than one rule with the same IF part, chose the rule that has maximum degree.
IF part | THEN part
--- | ---
$x_1$ | $x_2$ | $y$
N | N |
N | P |
P | N |
P | P |

Figure 8. The form of a fuzzy rule base.

The following defuzzification strategy was used to determine the output $y$ for given inputs $(x_1, x_2)$: first, we combined the antecedents of the $i$th fuzzy rule using product operation to determine the degree, $m_{O_i}^i$, of the output corresponding to $(x_1, x_2)$, i.e.,

$$m_{O_i}^i = m_{I_1}^i(x_1)m_{I_2}^i(x_2)$$

(11)

where $O^i$ denoted the output region of Rule $i$, and $I_j^i$ denoted the input region of Rule $i$ for the $j$th component, e.g., Rule 1 gave

$$m_{CE}^1 = m_{B_1}^1(x_1)m_{S_1}^1(x_2)$$

(12)

then, we used the following centroid defuzzification formula to determine the output

$$y = \frac{\sum_{i=1}^{K} m_{O_i}^i \bar{y}_i}{\sum_{i=1}^{K} m_{O_i}^i}$$

(13)

where $\bar{y}_i$ denoted the center value of region $O^i$ (for MF P, the center value is 1; for MF N, the center value is -1), and $K$ is the number of fuzzy rules in the combined fuzzy rule base.

**Experiment and data acquisition**

This study was approved by Institutional Review Board (IRB) of the University of North Carolina at Chapel Hill and with informed consent of the subjects. Two AB subjects
(two male subjects with height: 181cm and 183cm, and weight: 90kg and 93kg) and one TF subject (one male TF subject with height: 182cm, and weight: 84kg) participated in this study. Special socket and insole were used to help AB subjects walk on the powered knee prosthesis. Subject walked on the treadmill at 0.6 m/s. During the walking, a harness system was used for protection. The subjects were suggested to avoid holding the handrails as much as possible. Before the experiment, the subject took a 5-min walking trial with previously expert fine-tuned impedance parameter profile to warm up. In this study we used the same powered knee prosthesis and treadmill setup as in aim one.

An eight-camera motion analysis system (VICON, Oxford, UK) was used to capture the positions of 41 Reflective markers attached to the pelvis, torso, and both lower limbs. The sampling frequency of marker position was 1000 Hz. Raw marker positions were filtered using a second-order low-pass Butterworth filter with a cut-off frequency of 10 Hz. Before dynamic walking trials, a static standing trial was captured. Then the positions of markers on segment endpoints were used to calibrate a seven-segment (thigh, shank and foot for each limb, and pelvis) model for each subject. Clusters of three or four markers on rigid plates were attached to the pelvis, thigh and shank segments to track segment motion during walking on the treadmill. For the foot, a cluster of three markers was attached directly to the participants’ shoe. For the experiment on TF, one extra maker was put on T10 to evaluate the trunk swing during walking.
Figure 9. Marker label and position

Table 3. Marker label and position

<table>
<thead>
<tr>
<th>Label</th>
<th>Position</th>
<th>Label</th>
<th>Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>RIC</td>
<td>Right Iliac Crest</td>
<td>LIC</td>
<td>Left Iliac Crest</td>
</tr>
<tr>
<td>RTRO</td>
<td>Right Great Trochanter</td>
<td>LTRO</td>
<td>Left Great Trochanter</td>
</tr>
<tr>
<td>RKL</td>
<td>Right Knee Lateral</td>
<td>LKL</td>
<td>Left Knee Lateral</td>
</tr>
<tr>
<td>RKM</td>
<td>Right Knee Medial</td>
<td>LKM</td>
<td>Left Knee Medial</td>
</tr>
<tr>
<td>RAL</td>
<td>Right Ankle Lateral</td>
<td>LAL</td>
<td>Left Ankle Lateral</td>
</tr>
<tr>
<td>RAM</td>
<td>Right Ankle Medial</td>
<td>LAM</td>
<td>Left Ankle Medial</td>
</tr>
<tr>
<td>RCAL</td>
<td>Right Calcaneous</td>
<td>LCAL</td>
<td>Left Calcaneous</td>
</tr>
<tr>
<td>RTOE</td>
<td>Right Toe</td>
<td>LTOE</td>
<td>Left Toe</td>
</tr>
<tr>
<td>RTH</td>
<td>Right Thigh</td>
<td>LTH</td>
<td>Left Thigh</td>
</tr>
<tr>
<td>RSK</td>
<td>Right Shank</td>
<td>LSK</td>
<td>Left Shank</td>
</tr>
<tr>
<td>PV</td>
<td>Pelvis</td>
<td></td>
<td></td>
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</table>
For each trial, subject started walking with an initial impedance profile. There were eight different initial impedance profiles, shown in Figure 10, which consisted of either maximum or minimum value of each impedance parameter. Expert didn’t know the value of those initial parameters. During the walking, expert determined how much the impedance parameters were changed based on his observation on the walking performance of the subject. He told the experimenter who controlled the powered knee prosthesis the adjustment of the impedance parameters, and the experimenter adjusted the impedance parameter values and took a record. The expert was not allowed to know the value of the impedance parameters during the tuning. The tuning of impedance parameters was stopped when the expert was satisfied with the walking performance. Then subject kept walking for another 15 strides with the fine-tuned impedance profile. Subject took a 2-min rest after every trial.

Figure 10. Eight initial impedance parameter profiles. Blue dot indicated the position of initial impedance parameter profile in 3D impedance space, which were the corners in Figure 4
Numerical input-output data pairs were derived when expert changed the impedance parameters. Inputs of the data pairs were the differences between averaged knee parameters before tuning and their final values averaged from the 10 continues strides with fine-tuned impedance profile. Outputs of the data pairs were the changes of impedance parameter value tuned by the expert. All these data pairs were used to build the fuzzy rule base for each impedance parameter.

**Evaluation of the Expert Tuning Procedure**

The fine-tuned gait performance was compared with the initial gait performance. Different initial impedance parameter profiles would generate different knee joint angle profiles. Our hypothesis was that after expert’s tuning, the fine-tuned prosthetic knee joint angle profiles would be closer to AB’s knee joint angle profile. The prosthetic knee joint angle profiles from 10 continuous strides when subject walked with the initial impedance parameters and fine-tuned impedance parameters were normalized to 100 points and then averaged. They were compared with a normalized knee joint angle profile of AB [36]. Root mean squared of the error between the prosthetic knee joint angle profiles and AB knee joint angle profile was calculated. Paired t-test was used to compare the difference of the RMS before tuning and after tuning for each trial. P value was chosen as 0.05.

Stance and swing duration symmetry were calculated before tuning and after tuning. The beginning and end of stance phase (consisted of STF, STE and PSW) and swing phase (consisted of SWF and SWE) for each leg were determined by the vertical GRF, with a
threshold value of 5% body weight [37]. Raw force platform signals were collected and filtered with a second-order low-pass Butterworth filter with a cut-off frequency of 35 Hz. Symmetry index (SI) was calculated by (14), where \( S \) represented sound side measurement and \( P \) represented prosthetic side measurement. Perfect symmetric walking would have a SI value of zero. The closer the SI value was to zero, the more symmetric the gait was. Paired t-test was used to compare the SI before tuning and after tuning for each trial, and \( p \) value was chosen as 0.05.

\[
SI = \frac{(S-P)}{(S+P) \times 0.5}
\]

(14)

Step width and trunk movement were also measured before tuning and after tuning. For the trunk movement, peak-to-peak value in all three directions (lateral-medial, anterior-posterior, and superior-inferior) were calculated for each stride. Paired t-test was used to compare the step width and trunk movement before tuning and after tuning for each trial, and \( p \) value was chosen as 0.05.

**Results**

The fuzzy rule-bases generated through the learning of expert tuning procedure were shown in Appendix A, which included the rule-base for initial double support, single support, and swing extension phase. During the tuning, expert seldom tuned the impedance parameters in terminal double support and swing flexion phase, so there wasn’t enough data to build the rule-base for terminal double support phase and swing flexion phase.
Figure 11 showed the powered prosthesis knee joint angle profile before tuning and after tuning. (a, b) were for AB01, (c, d) were for AB02, and (e, f) were for TF. Black solid line showed the knee joint angle profile of AB, and colored dash line showed the powered prosthetic knee joint angle profile for each trial. Figure 12 showed that the difference between powered prosthetic knee joint angle profile and AB’s was significantly decreased after expert’s tuning.
Figure 11. Prosthetic knee joint angle before and after tuning. Black solid line represents the knee joint angle of the subject. Dashed color lines represents knee joint angle of different trials.
Figure 12. RMS of the error between powered prosthetic knee joint angle profile and AB’s normal walking knee angle before tuning and after tuning.

Figure 13 showed the difference of gait performance before and after expert tuning. The stance and swing duration symmetry were both significantly improved after tuning (stance duration: p<0.01; swing duration: p<0.01). For step width, after expert tuning, it was significantly decreased (p<0.01). Figure 13 (c) showed the difference of step width of TF subject as an example. In 7 of the 8 trials, the step width was decreased after tuning. Figure 13 (d) compared the trunk movement in lateral-medial, anterior-posterior, and superior-inferior directions under expert tuning. The trunk movement was significantly decreased after tuning (lateral-medial direction, p=0.04; anterior-posterior direction, p=0.01; superior-inferior direction, p=0.03).
Figure 13 Walking performance before tuning and after tuning. (a) showed the difference in stance/swing duration symmetry index, (b) showed the difference in step width, (c) showed the difference of step width in each trial of TF subject, and (d) showed the difference in trunk movement.
Discussion

During the tuning procedure, expert changed the impedance parameter values based on his observation of subject’s walking pattern, which included the powered prosthesis knee joint angle, gait symmetry, and also stability. The purpose of his tuning was to find a “good” impedance parameter profile, which could help the subject generate a natural walking pattern. The results showed that the fine-tuned powered prosthesis knee joint angle was closer to the AB’s knee joint angle than the initial powered prosthesis knee joint angle. Stance and swing duration symmetry were both improved after tuning. Step width was decreased after tuning, which meant the subject decreased his base of support and usually indicated improvement in stability. Based on these results, we could accept our hypothesis that by expert’s tuning, the subject’s gait performance was improved.

Though expert could tune the impedance parameters to improve the subject’s gait performance, the fine-tuned impedance parameters from different initial values were different. Figure 14 showed the fine-tuned stiffness, equilibrium position, and damping value in different gait phase. The fine-tuned impedance parameter values were scattered, which indicated that expert thought subject could generate a “good” walking pattern with a variety of impedance parameters. This variance came from two sources: inter-subject difference and intra-subject difference. For the inter-subject difference, the height and weight of each subject were different. For example, to support a heavier user, the stiffness value needed to be larger. When we apply the same impedance parameters to different subjects, they generated different gait pattern. On the other hand, to generate a natural gait pattern, the fine-tuned impedance
parameters for different subject were different. For inter-subject difference, the fine-tuned impedance parameters for each subject generated different gait performance. A large variance in the fine-tuned symmetry index, step width, and trunk movement could be observed in Figure 13.

During the tuning, expert mainly focused on tuning the impedance parameters in initial double support phase, single support phase, and swing extension phase, and seldom tuning the parameters in terminal double support phase and swing flexion phase. Terminal support phase was the shortest phase. The phase duration under different initial impedance parameter was 150±50 ms. It was difficult for expert to tell the difference in this phase. For Swing flexion phase, the purpose of knee flexion was to provide enough foot clearance during swing for the subject. The maximum swing flexion knee joint angle was 62±3 deg under different initial impedance parameters, which could provide enough foot clearance. And also the variance of the maximum swing flexion knee angle was also very small to be observed. Therefore, expert didn’t tune the parameter in this phase.
Figure 14. Fine-tuned impedance parameter value in initial double support, single support, and swing extension phases.
Conclusion

In this chapter the expert tuning procedure was studied to build fuzzy rules for the auto-tuning controller. Based on the result in previous chapter, numerical data-pairs were collected when expert changed the impedance parameters. Rule bases for initial double support, single support, and swing extension phases were built because expert only tuned the impedance parameter for these three phases. The subjects’ gait performance before and after expert tuning was also evaluated. After expert tuning, the powered prosthesis knee angle became closer to AB’s normal walking knee angle. Stance and swing duration symmetry was improved. Step width and trunk movements were also decreased. In conclusion, expert fine-tuned the impedance parameters in order to generate a more natural knee angle and better gait pattern for the subject.
AIM THREE: TESTING AND EVALUATION OF THE AUTO-TUNING SYSTEM

Introduction

Previously, the structure of auto-tuning system was discussed and rule bases for the fuzzy controller were built. In this chapter, we would test the auto-tuning system and evaluate the tuning performance. First, the structure of auto-tuning system needed to be modified based on the study of expert tuning procedure. To evaluate the tuning performance of auto-tuning system and compare it with expert tuning, the same subjects were recurred in the study and the same initial impedance parameters were applied to the test of auto-tuning system. While the expert’s tuning target was to generate a natural knee angle and better gait performance, the auto-tuning system’s target was only to match AB’s normal walking knee angle. Therefore, our hypothesis was that the powered prosthesis knee angle generated by auto-tuning would be closer to AB’s normal walking knee angle than that of expert tuning, but the fine-tuned gait performance was not as good as that of expert tuning.

Material and Method

Architecture of the Auto-tuning System

Figure 15 shows the modified architecture of the powered knee prosthesis control with auto-tuning system based on previous study. The Buffer block in the system stored the data collected from powered knee prosthesis, including knee joint angle, angular velocity, and GRF.
The Buffer size was set as 5 strides, which was the minimum number of stride for expert tuning. Another difference between Figure 15 and Figure 5 was the outputs of Auto-tuning Controller. In our previous design, the Auto-tuning Controller would tune the impedance parameter value for all five gait phases. But based on the results in previous study, we found expert seldom tuned the impedance parameters in terminal double support phase and swing flexion phase. Therefore, the modified Auto-tuning Controller only consisted of three fuzzy controllers for initial double support phase, single support phase, and swing extension phase, and the outputs of Auto-tuning Controller were the change of impedance parameters for these three gait phases.
Figure 15. The architecture of powered knee prosthesis control with auto-tuning system. The finite-state machine consisted of five states. $\theta_p$ and $\dot{\theta}_p$ represented knee joint angle, angular velocity, respectively.

**Experiment and evaluation**

This study was approved by Institutional Review Board (IRB) of the University of North Carolina at Chapel Hill and with informed consent of the subjects. The same subjects participated in this study as in aim two. Special socket and insole were used to help AB subjects walk on the powered knee prosthesis. Subject walked on the treadmill at 0.6 m/s. During the walking, a harness system was used for protection. The subjects were suggested to avoid
holding the handrails as much as possible. The powered knee prosthesis setup and marker configuration were the same as the study in aim two, which was described in the previous chapter.

During the experiment, for each trial, subject started walking with an initial impedance profile. Eight different initial impedance profiles were chosen as the eight corners of Figure 10, which consist of either maximum or minimum value of each impedance parameter. For each initial impedance profile, we conducted two trials: one without auto-tuning, and one with auto-tuning. The order of all 16 trials was randomized. For those trials without auto-tuning, subject would walk with the initial impedance profile for 2 minutes. For those trials with auto-tuning, subject would walk with the initial impedance profile for about 30 seconds, then the auto-tuning controller was activated. The auto-tuning controller checked the input measurements for every 5 strides. If there was a missing step in the middle, or the variance of the measurement exceeded the variance of normal walking, then the auto-tuning would not change the impedance parameters and wait for the next 5 strides. If there was not missing step and measurement variance was small, the auto-tuning system would update the impedance values. The criteria used by expert to stop his tuning procedure were unknown, so we could not apply the same criteria for the auto-tuning system. The prosthesis knee angle was compared with the target trajectory to determine whether the auto-tuning was terminated. If the maximum error of the peak knee angles was smaller than the 1.5 standard deviation of the knee trajectory, then the auto-tuning was terminated. Then the subject took another 15 strides with the fine-tuned impedance parameters.
**Evaluation of the Auto-Tuning Procedure**

The evaluation of the auto-tuning procedure was similar to the evaluation of expert tuning procedure. We compared the powered prosthesis knee angle, stance/swing duration symmetry, step width, and trunk swing before the tuning and after the tuning. And since the testing condition for both tuning methods were the same (same subjects walking with same initial impedance parameters), the fine-tuned gait performance of these two methods were also compared. For powered prosthesis knee joint angle, because the target of auto-tuning system was AB’s knee joint angle, we hypothesized that was that the auto-tuning fine-tuned powered prosthesis knee joint angle was closer to AB’s than expert tuning result, and both of the fine-tuned powered prosthesis knee joint angle were closer to AB’s compared to initial knee joint angle. The prosthetic knee joint angle profiles from 10 continuous strides when subject walked with the initial impedance parameters and fine-tuned impedance parameters were normalized to 100 points and then averaged. They were compared with a normalized knee joint angle profile of AB. Root mean squared of the error between the prosthetic knee joint angle profiles and AB knee joint angle profile was calculated. Paired t-test was used to compare the difference of the RMS before tuning and after tuning for each trial and to compare the fine-tuned prosthesis knee angle of auto-tuning method and expert tuning method. P value was chosen as 0.05.

Stance and swing duration symmetry under three different conditions: initial gait performance, expert fine-tuned performance, and auto-tuning fine-tuned performance, were also evaluated. Symmetry index (SI) was calculated by (15), where $S$ represented sound side
measurement and $P$ represented prosthetic side measurement. Perfect symmetric walking would have a SI value of zero. The closer the SI value was to zero, the more symmetric the gait was. Paired t-test was used to compare the SI before tuning and after tuning for each trial, and to compare the fine-tuned SI of auto-tuning method and expert tuning method. P value was chosen as 0.05.

\[
SI = \frac{(S-P)}{(S+P) \times 0.5}
\]  

(15)

Step width and trunk movement were also measured before tuning and after tuning. For the trunk movement, peak-to-peak value in all three directions (lateral-medial, anterior-posterior, and superior-inferior) were calculated for each stride. Paired t-test was used to compare the step width and trunk movement before tuning and after tuning for each trial and to compare the difference between fine-tuned performance of auto-tuning method and expert tuning method. P value was chosen as 0.05.

**Results**
Figure 16. Powered prosthetic knee joint angle under different conditions
Figure 16 showed the powered prosthesis knee joint angle of the TF subject with auto-tuning and without tuning. After auto-tuning, the powered prosthesis knee joint angle became closer to the target trajectory. The prosthesis knee angles were different from the target for the trials without tuning. Figure 18 showed the powered prosthesis knee joint angle of the two AB and one TF subject under different conditions. Figure 18 (a, b, c) showed the powered prosthesis knee joint angle of AB01, AB02, and TF before tuning; Figure 18 (d, e, f) showed the powered prosthesis knee joint angle of AB01, AB02, and TF after expert’s tuning; and Figure 18 (g, h, i) showed the powered prosthesis knee joint angle of AB01, AB02, and TF after auto-tuning. For both expert tuning and auto-tuning, the fine-tuned powered prosthesis knee joint angles were closer to the AB normal walking knee angle. Compared with expert tuning result, the auto-tuning fine-tuned knee angles from different initial impedance parameters had smaller variance. Figure 19 showed root mean square error between powered prosthesis knee angle and AB normal walking knee angle. For both tuning methods, the error was significantly decreased (expert tuning: p<0.01; auto-tuning: p<0.01). Though there was no significant difference between the error of expert tuning result and auto-tuning result, the error of auto-tuning result was smaller and had a smaller variance.
Figure 20 showed the difference in stance/swing duration symmetry under different conditions. For both tuning methods, the absolute value of stance and swing duration symmetry index was significantly decreased (for stance duration SI, expert tuning: \(p<0.01\), auto-tuning: \(p<0.01\); for swing duration SI, expert tuning: \(p<0.01\), auto-tuning: \(p<0.01\)), which indicated a more symmetric gait pattern. Comparing the fine-tuned results of expert tuning and auto-tuning, the mean value of stance duration symmetry index of expert tuning result was smaller than auto-tuning’s, and the mean value of swing duration symmetry index of expert tuning result was larger than auto-tuning’s, though the differences were not significant.
Figure 17. Powered prosthetic knee joint angle under different conditions. Black solid line represents the knee joint angle of the subject. Dashed color lines represents knee joint angle of different trials.
Figure 18. continued

(g) AB01 after auto-tuning
(h) AB02 after auto-tuning
(i) TF after auto-tuning
Figure 19. Compare the root mean square error between powered prosthesis knee angle and AB normal walking knee angle under different conditions.

(a) Stance duration symmetry index  (b) Swing duration symmetry index

Figure 20. Compare the stance/swing duration symmetry under different conditions.

The step widths under different conditions were shown in Figure 21. For both tuning methods, the fine-tuned step width was significantly decreased (expert tuning: p<0.01; auto-tuning: p<0.01). The mean value of expert fine-tuned step width was smaller than auto-tuning’s, but the difference was not significant. Figure 22 compared the trunk movement in
lateral-medical, anterior-posterior, and superior-inferior directions under different conditions. For expert tuning, the trunk movement was significantly decreased after tuning (lateral-medial direction, \( p=0.04 \); anterior-posterior direction, \( p=0.01 \); superior-inferior direction, \( p=0.03 \)). But for auto-tuning, in lateral-medical and anterior-posterior direction, the trunk movement was increased after tuning; only in superior-inferior direction the trunk movement was decreased. The difference of trunk movement before and after tuning was not significant.

Figure 23 compared the fine-tuned impedance parameter value of expert tuning and auto-tuning. The coordinate of the blue dot was the fine-tuned impedance parameter value of two different methods for the same subject from the same initial impedance parameter profile. Figure 23 (a) compared the stiffness value. The regression equation of the fine-tuned damping value was \( y = 0.916x + 0.090 \) with \( R^2 = 0.956 \). Figure 23 (b) compared the equilibrium position value. The regression equation of the fine-tuned damping value was \( y = 0.759x - 0.489 \) with \( R^2 = 0.317 \). Figure 23 (c) compared the damping value. The regression equation of the fine-tuned damping value was \( y = 0.827x - 0.002 \) with \( R^2 = 0.866 \).
Figure 21. Compare the step width under different conditions

Figure 22. Compare the trunk movement in lateral-medial, anterior-posterior, and superior-inferior directions under different conditions.
Figure 23. Compare of fine-tuned impedance parameter value of expert tuning and auto-tuning:

(a) Expert fine-tuned stiffness value Vs. Auto-tuning fine-tuned stiffness value

(b) Expert fine-tuned equilibrium position Vs. Auto-tuning fine-tuned equilibrium position

(c) Expert fine-tuned damping Vs. Auto-tuning fine-tuned damping
Discussion

Auto-tuning controller was built to mimic the tuning procedure of expert. The target of auto-tuning controller was the normal walking knee angle of AB. Based on the result, the auto-tuning controller could fine-tune the impedance parameters and generate a powered prosthesis knee angle which was close to the normal walking knee angle of AB. Compared with the expert fine-tuned powered prosthesis knee angle, the auto-tuning controller’s result was closer to the target, and the variance between different trials was also smaller. And this change was most probably due to the auto-tuning system, instead of user adaptation. After the auto-tuning controller’s tuning, the subject’s gait became more symmetric. Both stance and swing duration symmetry were improved. Subject also decreased his step width, which represented the base of support, after tuning.

Unlike these parameters, the trunk movement was not improved after tuning. The trunk movements in both lateral-medial and anterior-posterior directions were increased, which indicated a larger swing of trunk during walking. It was observed in the results that though there was no significant difference, the averaged auto-tuning fine-tuned gait performance was worse than that of expert tuning. The difference in tuning target might explain this result: for auto-tuning, the target was to generate a normal powered prosthesis knee angle; for expert tuning, the expert didn’t only focus on powered prosthesis knee angle, but also observe the subject’s walking pattern, which including gait symmetry and stability. Therefore, only targeting a normal powered prosthesis knee angle might not guarantee a better gait pattern.
The fine-tuned impedance parameter values for expert tuning and auto-tuning were different from each other, shown in Figure 23. The fine-tuned stiffness values for both methods were close, with $R^2 = 0.956$. The auto-tuning fine-tuned damping value was smaller than expert fine-tuned value ($y = 0.827x - 0.002$), but also had a high correlation coefficient ($R^2 = 0.866$). On the other hand, the fine-tuned equilibrium position values were not strongly correlated ($R^2 = 0.317$), which might due to the difference in the fine-tuned powered prosthesis knee angle. The expert fined-tuned powered prosthesis knee angles had a large variance compared with the auto-tuning result. Based on previous result, equilibrium position value was strongly related to the peak knee angle. Therefore, the expert fine-tuned equilibrium position values had a large variance compared with the auto-tuning values.

**Conclusion**

Auto-tuning controller was tested and compared with expert tuning procedure in this chapter. With the auto-tuning controller, the impedance parameters could be automatically tuned during walking to generate a powered prosthesis knee angle, which was close to AB normal walking knee angle. After auto-tuning, stance and swing duration symmetry was improved, and step width was decreased, while the trunk swing range was increased. The auto-tuned gait performance was not as good as expert tuned gait performance, which implied that only targeting a normal powered prosthesis knee angle might not guarantee a better gait pattern.
CONCLUSION

Currently, most powered prostheses use a finite state impedance controller to control the prosthetic joint angles. Due to the inter-user difference, the impedance parameters need to be fine-tuned for each user. This tuning procedure is usually conducted by an expert, which is time and resource intensive. Therefore, any approach to automate and shorten the tuning procedure would have positive clinical impact.

The goal of this work is to build an auto-tuning system, which can mimic expert tuning procedure, to replace the expert. Currently we do not fully understand the relationship between impedance control parameters and powered prosthesis gait performance. However, there is already a controller in place to effectively tune the impedance parameters: the human expert. Therefore, we learn from the expert tuning procedure and build an automate system with the similar function. The whole work was divided into three aims. For aim one, we figured out that the powered prosthesis knee angle parameters could be used as the input for impedance parameter tuning. For aim two, by studying the expert tuning procedure, we found that expert only tuned the impedance parameters in initial double support, single support, and swing extension phase. The fuzzy tuning rule-base was built for the impedance parameters in these three phases. After expert’s tuning, the powered prosthesis knee angle became closer to AB’s normal walking knee angle. Stance and swing duration symmetry was improved, step width was decreased, and trunk swing range was also decreased.

In aim three, we built the auto-tuning system and tested its performance on two AB and one TF subjects. With the auto-tuning controller, the impedance parameters could be
automatically tuned during walking. The fine-tuned powered prosthesis knee angles were closer to AB’s normal walking knee angles compared with expert tuning result. But the fine-tuned gait performance was not as good as expert fine-tuned performance, which implied that only targeting a normal powered prosthesis knee angle might not guarantee a better gait pattern. Therefore, future studies are needed to determine the additional parameters related to gait performance that should be monitored while tuning the impedance control parameters.

One of the limitations of our work was the limited number of subjects. Currently the auto-tuning controller was built based on the data collected from two AB and one TF. More subjects needed to be recurred in the future. Another limitation was the auto-tuning controller only tuned impedance parameters in initial double support, single support, and swing extension phase. This might be enough for tuning the powered prosthesis to negotiate level ground walking. But if the user want to walk on ramp and staircase with powered prosthesis, then the impedance parameters in the rest two phases needed to be fine-tuned as well.
REFERENCES


APPENDICES
Appendix A. Fuzzy rule bases for initial double support, single support, and swing extension phases

Table A 1. Fuzzy rule bases obtained from expert tuning procedure

(a) Fuzzy rule bases for tuning stiffness in initial double support phase

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(b) Fuzzy rule bases for tuning equilibrium position in initial double support phase

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(c) Fuzzy rule bases for tuning damping in initial double support phase

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(d) Fuzzy rule bases for tuning stiffness in single support phase

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(e) Fuzzy rule bases for tuning equilibrium position in single support phase

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(f) Fuzzy rule bases for tuning damping in single support phase

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(g) Fuzzy rule bases for tuning stiffness in swing extension phase

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(h) Fuzzy rule bases for tuning equilibrium position in swing extension phase
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(i) Fuzzy rule bases for tuning damping in swing extension phase

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