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User Controlled Interface for Tuning Robotic Knee Prosthesis

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***Abstract*—The tuning process for a robotic prosthesis is a challenging and time-consuming task both for users and clinicians. An automatic tuning approach using reinforcement learning (RL) has been developed for a knee prosthesis to address the challenges of manual tuning methods. The algorithm tunes the optimal control parameters based on the provided knee joint profile that the prosthesis is expected to replicate during gait safely. This paper presents an intuitive interface designed for the prosthesis users and clinicians to choose the preferred knee joint profile during gait and use the autotuner to replicate in the prosthesis. The interface-based approach is validated by observing the ability of the tuning algorithm to successfully converge to various alternate knee profiles by testing on two able-bodied subjects walking with a robotic knee prosthesis. The algorithm was found to converge successfully in an average duration of 1.15 min for the first subject and 2.31 min for the second subject. Further, the subjects displayed different preferences for optimal profiles reinforcing the need to tune alternate profiles. The implications of the results in the tuning of robotic prosthetic devices are discussed.**

I. Introduction

Robotic prostheses are gaining increasing prevalence among people with amputations due to their active torque production capability to perform various tasks in a natural way[1]. Conventional passive prostheses used currently fail to actively input the energy into the joints during locomotion, severely impeding natural gait. In contrast to such passive devices, robotic prostheses help lower limb amputees to achieve a normative gait replication by delivering active power input. Studies have shown that active devices decreased metabolic consumption during level-ground walking [2, 3] and enhanced stability and balance [4, 5]. In addition, these devices are shown to adapt to different terrains [6, 7].

Several control methods have been implemented to control active lower limb prostheses and orthotic devices ranging from simple push-off controllers to neuromuscular models [8]. Of these controllers, the finite state machine (FSM) impedance control scheme is one of the most used approaches in research and commercial applications [6, 9]. The FSM-based impedance controller consists of several states, each of which has its own realization of impedance controller with specific impedance parameters [9-11] that need to be tuned for optimal operation. The current approach for tuning is performed by a clinician based on empirical observations and qualitative feedback from the user. The process is often challenging, time-consuming, and heavily reliant on the clinician's expertise, potentially leading to inconsistent results [11, 12].

To address the limitations of the manual tuning process, an autotuning approach using reinforcement learning has been proposed specifically for robotic lower limb prostheses [13]. The algorithm has been validated on a robotic knee prosthesis. The autotuning algorithm tunes the impedance parameters of each state with the goal of recreating the knee profile observed during the normal gait of able-bodied subjects [14]. The autotuning approach has been successfully demonstrated on transfemoral amputees using the robotic knee prosthesis [15]. However, it is an open question whether tuning the prosthesis control parameters to replicate knee profile observed in able-bodied people yields an optimal gait and preference in the amputee users. Since gait biomechanics of transfemoral amputees is affected by the physiological changes due to amputation and loss of proprioceptive feedback from the prosthesis, duplicating normative gait kinematics might not be the goal of amputee users. Moreover, the properties of the prosthetic foot used in the prosthesis are also found to affect the gait biomechanics and preferred gait pattern.

Now the question is whether the policy learned by reinforcement learning is capable of adapting to the preferred knee profile of amputee users and, more importantly, how to define the optimal and user-preferred prosthesis control in gait during the prosthesis tuning process. One intriguing idea is to give the prosthesis user the freedom to choose the knee control parameters. This concept has been investigated by several groups. However, they only considered semi-active devices maintaining constant stiffness throughout the gait cycle [16] or focused on simulating various available passive devices [17]. In most FSM impedance control with over 9 parameters to tune for each gait cycle, designing a user tuning interface is challenging and has several requirements. (1) The interface must be user-friendly to provide an intuitive way for adjusting the robotic knee behavior as desired. (2) The interface-controller complex must be safe to use since inappropriate control can lead to instability in gait. In addition, (3) the interface must be time-efficient to achieve the tuning goal since longer tuning time brings extra fatigue and pain for prosthesis users. Thus, the direct provision of tuning many impedance values to the user might confuse the user with no technical background.

This study aimed to develop a new user-controlled interface (UCI) that allowed the user to define the desired prosthesis knee impedance control efficiently and safely (Fig.

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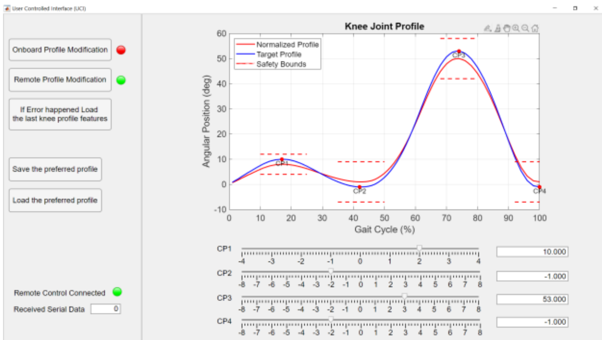

Fig. 1. A screenshot of the UCI. The NKK profile displayed in red while the adjustable profile is denoted in blue. Safety bounds are provided for the subject to ensure safe exploration of various profiles.

1). This design was combined with our previous RL based prosthesis auto-tuning algorithm that can tune prosthesis impedance parameters to meet the desired normative knee motion. Nevertheless, we do not know whether the auto-tuning algorithm can quickly adapt to varied knee motion targets defined by the user interface. Hence, before testing with the amputee population, the feasibility of the approach was verified based on two conditions: 1) if the autotuning algorithm can tune the impedance parameters to different knee profiles in reasonable duration without endangering the safety of users, and 2) if the subjects can perceive the differences between the profiles to select the optimal knee profile.

Our main contribution includes (1) a new UCI platform that allowed the prosthesis user to intuitively customize the robotic prosthesis control, (2) integration of the UCI to the previously developed RL-based automatic prosthesis impedance tuning system, (3) validation of the robustness of RL algorithm policy in adapting to various knee profiles for different users, and (4) preliminary validation of the UCI on two able-bodied subjects as a precursor to testing with amputee populations.

II. Methods

The aim of the paper was to develop a user-controlled interface that is intuitive, efficient, and safe to define the desired prosthesis control by the user. We validated its utility in obtaining a user-preferred profile for autotuning of the prosthesis controller using reinforcement learning. This section describes the reinforcement learning-based prosthesis tuning algorithm, the user interface, and the experiment designed to validate the approach using a robotic knee prosthesis.

A. *Reinforcement Learning based autotuning*

One of the biggest challenges of the finite state impedance controller is to find the optimal impedance parameters (stiffness, damping, and equilibrium angle) for each state of the controller. In our previous work, we have proposed an approximate policy iteration-based RL approach as a solution to overcome this challenge [18], which was used as a basis for this study. To implement the RL algorithm, the human-prosthesis system is formulated as a discrete-time nonlinear system as follows,

$$x_{k+1} = F(x_k, u_k),\ k = 0, 1, 2, \ldots \tag{1}$$

$$u_k = \pi(x_k) \tag{2}$$

where each impedance control parameter update is accomplished with the k discrete time step. State and action vectors at time k are presented as $x_k \in R^2$ and $u_k \in R^3$ where F represents unknown system dynamics. The control policy is $\pi\colon \in R^2 \rightarrow R^3$. At each time step, a stage cost, $U(x_k, u_k)$, is assigned to indicate how well a state-action pair performs. For effective real-time control, the stage cost is formulated in a quadratic form as shown in (3),

$$U(x_k, u_k) = x_k^T R_x x_k + u_k^T R_u u_k \tag{3}$$

where $R_x \in R^{2\times2}$ and $R_u \in R^{3\times3}$ are positive definite weight matrices. In addition, the cost-to-go function of $Q(x_k, u_k)$ is defined as

$$Q(x_k, u_k) = U(x_k, u_k) + \sum_{j=k+1}^{\infty} \gamma^{j-k} U\left(x_j, \pi(x_j)\right) \tag{4}$$

with the discount factor of γ. Let the current policy be π and the Q value be in (4). It should be noted that the system shown in (1) reaches x_{k+1} after u_k is applied at state x_k and the control policy π is followed thereafter.

The Bellman optimality equation is used as a benchmark for the optimal cost function of

$$Q^*(x_k, u) = U(x_k, u) + \gamma Q^*\left(x_{k+1}, \pi^*(x_{k+1})\right) \tag{5}$$

where the optimal control policy $\pi^*(x_k)$ can be found by

$$\pi^*(x_k) = \underset{u_k}{\operatorname{argmin}}\, Q^*(x_k, u_k) \tag{6}$$

Bellman optimality equation shown in (5) is iteratively solved through policy iteration as detailed in [18].

While implementing the algorithm, the state and action weight matrices were designed to prioritize the peak error within the cost function since the peak error is more responsive to phase parameter changes than duration error, which is dependent on the human gait pattern. Convergence is achieved when the error between normative knee kinematics (NKK) and robot knee kinematics is within the bounds in each of the four phases for the tuned impedance

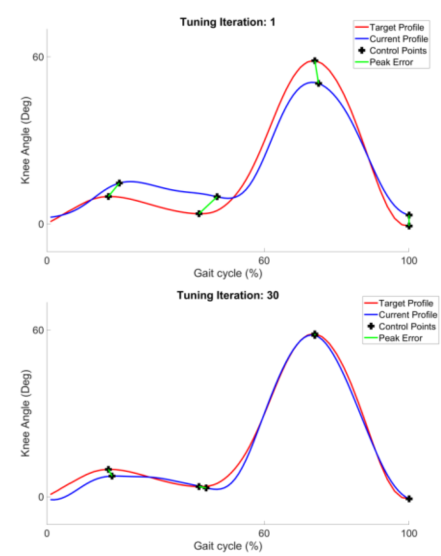

Fig. 2. Functioning of the RL algorithm. The error in the peak points is used in the reward function to generate the new profile. The plot on the top shows the difference between observed knee profile and target knee profile at the beginning of the trial and the bottom plot shows the comparison at after convergence.

parameters. The error bounds for the algorithm were set as 2º spatially and 2% of gait cycle time temporally.

In this study, the robustness of the policy obtained through the RL algorithm to changes in knee profile as preferred by the users is analyzed. The algorithm was implemented in MATLAB and was integrated to work in real-time with the finite state controller implemented in LabVIEW.

B. *Design of User Controlled Interface*

The control interface was designed to allow the subject to intuitively alter the knee kinematics based on their preference. The interface displays NKK of able-bodied subjects in red and the adjustable knee profile in blue. The control points for each phase (CP1-CP4) can be adjusted based on the user's preferences to generate a profile for the autotuning algorithm. The interface facilitates two ways of modifying the knee profile for tuning. The first method was onboard profile modification, in which the sliders provided in the interface can be used to adjust the location of the control points.

Additionally, a remote profile modification was provided for the users to modify the profile while they are interacting with the robotic prosthesis. An infrared remote control coupled with Arduino Mega 2560 was used for remote profile modification. The position of each control point can be altered by pressing the corresponding number on the remote followed by up and down arrows. It should be noted that the temporal locations of the control points are fixed. Experimentally derived safety bounds have been implemented into the system to avoid risks of fall due to abnormal profiles. The safety bounds were represented in the interface through dashed lines. A safety bound of ±4º from NKK was chosen for the first control point and ±8º for the other three control points to ensure safety while also ensuring sufficient range for users to explore modified profile characteristics.

The knee profile generated by the UCI relying on the user's preferences was then loaded into the LabVIEW. LabVIEW, in turn, continuously runs the high-level RL-based autotuning algorithm and low-level impedance controller within the FSM framework to control and tune the robotic knee prosthesis (Fig. 3). The tuned controller then consists of optimal impedance values for all four sequential gait phases such that

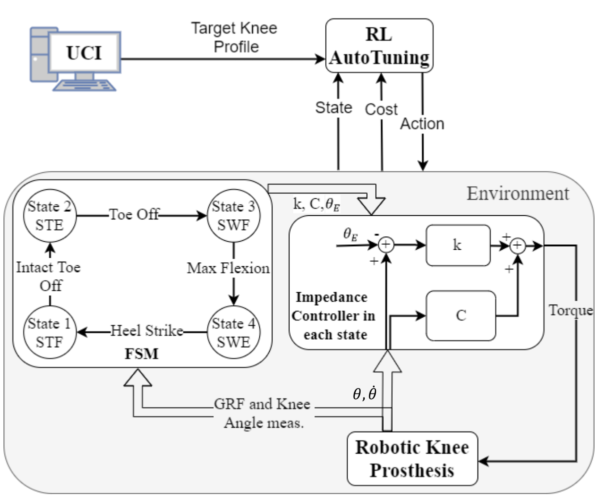

Fig. 3. The hierarchical design architecture of the system.

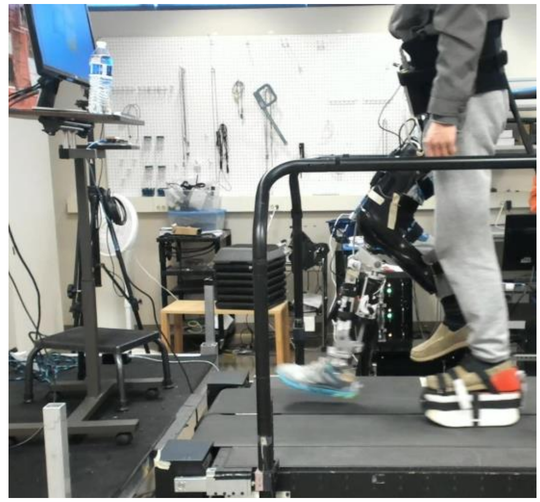

Fig. 4. The experimental setup for validation of the UCI approach. The robotic prosthesis is attached through an adapter to the right limb of the able bodied subject. The interface is displayed on the screen in front of the subject to facilitate modification of the knee profile.

the knee profile follows the profile set through the control points.

C. *Experimental setup and protocol.*

A pilot study was conducted to verify the feasibility of the UCI approach on two able-bodied subjects with no prior neurological or physiological conditions. The study was conducted with the approval of the Institutional Review Board of the NC State University, with both subjects providing informed consent. The experimental setup consisted of the robotic prosthesis, a visual display for UCI, and a Bertec treadmill on which the subjects, wearing the robotic prosthesis via an adaptor (Fig. 4), were instructed to walk at a constant speed of 0.6 m/s during the trials. The purpose of the study was to verify if the algorithm can converge to different knee profiles chosen by subjects robustly and safely within a reasonable time. In addition, we examined if the subjects could perceive the differences between the profiles. So, the experiment was divided into two parts: the tuning trials and the comparison trials.

The purpose of the tuning trials was to verify if the tuning algorithm can successfully converge to the user-specified profile within a reasonable time. To verify the convergence, the first trial was performed with the normalized knee kinematics. The subject was then asked to vary the first control point (CP1) above and below the normalized knee profile by a fixed value for the next two trials while the other three control points were maintained at the NKK profile. The final two trials are then conducted by varying CP2 while the other three points are maintained at the NKK level. Each tuning trial was run for a maximum of 6 minutes, in intervals of 2 min. A 2 min rest was provided to the subjects after every 2 min interval of walking to prevent fatigue.

The tuning trials had to be limited to 5 trials to prevent fatigue in the subjects and to perform the experiment within a reasonable duration. The first two control points were chosen since the previous study showed that the prosthesis user was more sensitive to changes in controller impedance in the stance phase [19]. The tuning for each modified profile was performed with a predetermined fixed starting point. Additionally, the tuning was also performed by using the last profile tuned values as the starting point to analyze the convergence of the algorithm.

The purpose of the comparison trials was to observe if the subjects perceive any differences between the different knee profiles when the profile was altered across the control point. For the two control points considered the study, the above and below variation conditions were compared with each other as well as the NKK profile. So, for each control point, there were 6 pairs of comparisons resulting in 12 comparison trials. For each comparison trial, the subject was asked to walk on the treadmill while the robot simulated the tuned values of the first profile for 40 sec followed by the second profile for 40 sec. The order of the comparison pairs was randomized to reduce bias. Further, to prevent fatigue, 2 min of rest was provided after every two trials.

III. Results

Prior to the prosthesis tuning session, each subject's opinion on the interface's ease of use was evaluated. Both subjects reported the operation of the interface to be intuitive and straightforward. We also studied the effectiveness and efficiency of our UCI system for tuning prosthesis control. The effectiveness of the UCI approach was evaluated by the convergence behavior of the autotuning algorithm to meet the user-defined knee kinematics in gait as well as the ability of subjects to perceive the differences between profiles. Efficiency was estimated through the duration needed for the autotuning algorithm to meet the desired values.

A. Autotuning convergence and efficiency

The convergence criteria for the algorithm were to have the four control points of the knee profile to be within 2º of the target control points and within 2% temporally. Based on the above criteria, the autotuning algorithm achieved convergence across all conditions for both subjects. Further, the amount of time required to converge was evaluated for each profile tuning. When the tuning was performed with random predetermined initial parameters for the subjects, the average time was found to be 4.1 and 3.24 min, respectively, for each subject. Additionally, once the autotuning was performed for the NKK profile, the tuned parameters were used as the starting point for the altered profiles. The duration for autotuning from these starting parameters was observed to be 1.15 and 2.31 min, respectively. Fig. 5 shows the convergence behavior across all tuning trials for a representative subject from a random starting point. Fig. 6 shows the convergence behavior of the same representative subject for tuning using previously tuned parameters as a starting point. It is interesting to note that a change in one control point results in errors in the other control points, which indicates the possible association of impedance parameters across phases during tuning.

B. Perception of altered knee profiles and user safety

To evaluate whether subject could perceive differences between the profiles, pair wise comparisons were performed

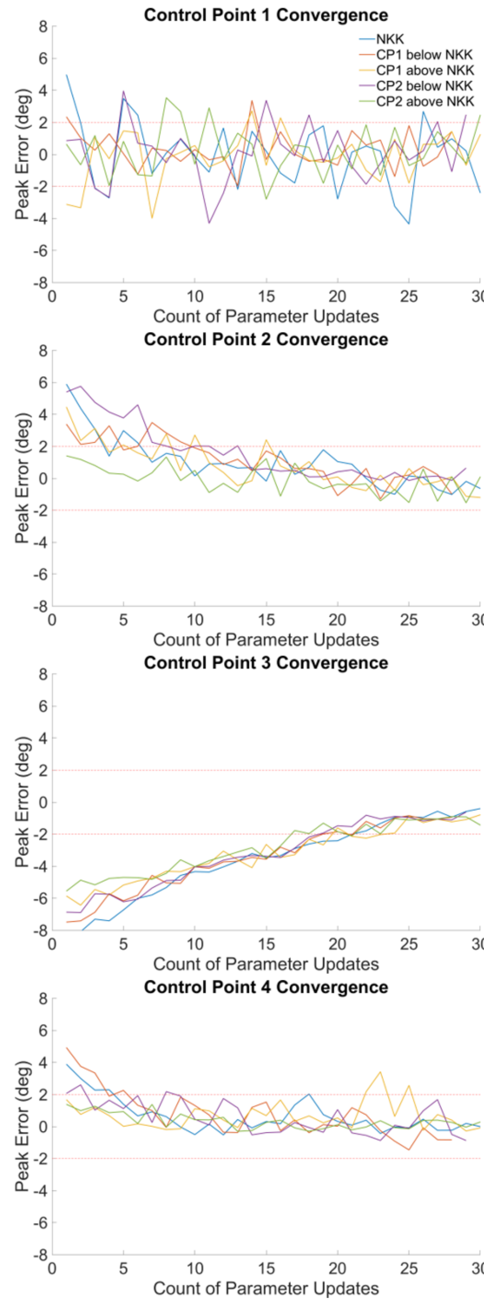

Fig. 5. The observed error plots of each control point during tuning across different profiles for a representative subject when tuning is performed from a random starting point. The plots show that the prosthesis knee profiles converges to the target in all the tuning trials in under 30 iterations.

between altered profiles at each control point and with the NKK profile. Subject 1 preferred altered profiles over NKK, with a slight preference for hyperextension of the knee (reduced CP angle) at both control points. Subject 2 preferred the NKK profile over the altered profiles with no apparent preference for either altered profile when compared together. While there was no apparent relationship between control point angle and the preference of the subjects, the comparison trials showed that each subject has their own individual preference for the optimal knee profile, which might not necessarily be the NKK profile. The profile preference of each subject during pairwise comparisons is shown in Table

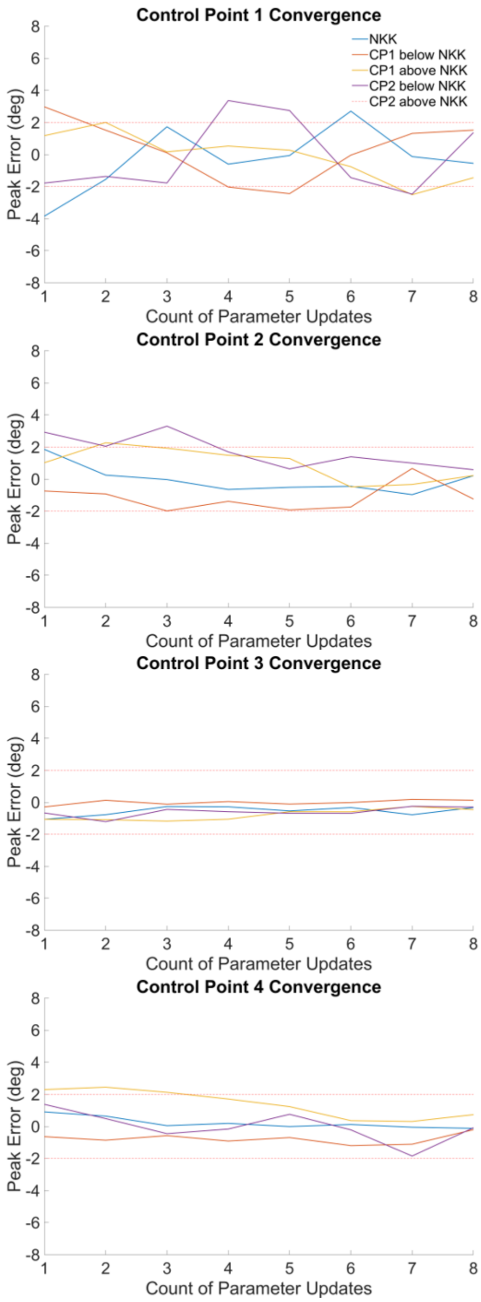

Fig. 6. The observed error plots of each control point for a representative subject when tuning is performed using parameters of previous tuned profile. The plots show that the prosthesis knee profiles converges to the target in all the tuning trials in under 8 iterations.

TABLE 1. THE PROFILE PREFERENCE OF THE SUBJECTS IN PAIRWISE COMPARISONS

	Subject 1		Subject 2	
	CP1	*CP2*	*CP1*	*CP2*
NP vs CP ↑	≈	CP↑	NP	NP
NP vs CP ↓	CP ↓	≈	NP	NP
CP↑ vs CP ↓	≈	CP ↓	≈	CP↓

NP: Normative profile; CP: control point; ↑: increase;↓:decrease
≈: No differentiation in preference

1. More importantly, neither of the subjects reported a sense of instability in balance either during comparison or during the tuning process, partly due to limits set on maximum errors from control points and safety bound used in our reinforcement learning algorithm [18].

IV. Discussion

In this study, we present an intuitive UCI that enables the robotic prosthesis users to tune a robotic powered knee prosthesis based on their own preference. The proposed platform simplifies the complex process of tuning a large number of impedance parameters, generally performed by certified clinicians under strict timing and fatigue related limitations. This UCI empowers amputees by giving them control of their device. The utility of the approach is based on two main factors: 1) if the autotuning algorithm can safely and successfully configure the impedance parameters based on user inputs in a reasonable time, and 2) if the user can perceive the differences in robotic mechanics and relate it to the changes made through the interface. This platform can be used to investigate user preference in prosthesis mechanics and be potentially used as a clinical tool for prosthesis control personalization.

A. Performance of the UCI approach

To verify if the autotuning algorithm could efficiently converge to the user preferred profiles, profiles with alterations in control points 1 and 2 were chosen. As observed in the results, the algorithm ensured user safety while the impedance parameters converged for both subjects under 4.1 minutes, showcasing the ability of the learned policy to adapt to changes in knee profile. The subjects did perceive differences in profiles and were not adversely affected by changes to the robotic knee profile. The tuning process converged in 4 min, which outperforms the time taken by manual tuning methods to meet the desired knee kinematics during gait. However, an additional amputee tests are needed to quantify the performance of the policy in achieving their desired prosthesis performance. The tuning time can be further reduced by using optimal initial set of control parameters. During the study, the tuned parameters of the prior profile were used as initial parameters for the next profile. This approach led to convergence at an average time of 1.15 and 2.31 min for the subjects (Fig. 7). As selecting optimal initial parameters could further reduce tuning time, the users would have an increased chance to explore multiple knee profiles to choose a personally optimal profile.

B. Implications for amputee populations

The results showed that the two subjects demonstrated different preferences for the knee profile. Ideally, they would have preferred the NKK profile since it is based on able-bodied subject's knee profile. The preference might have been related to the socket attachment design or due to the difference in ankle joint behavior of the robotic prosthesis. These effects could be more pronounced in amputee populations due to further variations in residual limb as well as socket attachments and lack of proprioceptive feedback. Hence, there is a strong possibility that the optimal knee profile of

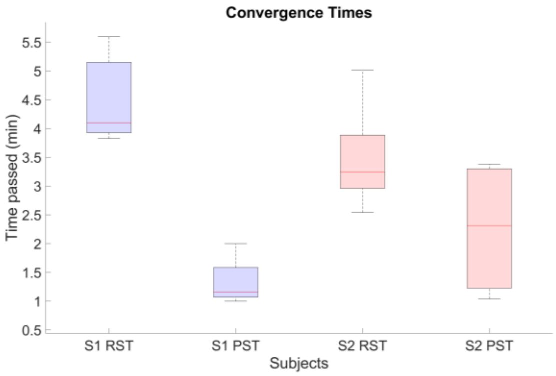

Fig. 7. The comparison of convergence times for two subjects when the tuning was performed with random starting parameters (RST) and predetermined starting parameters (PST). The PST for the current study were chosen as the tuned parameters of the previous trial.

amputee populations is different from the NKK.

In general finite state controllers have 9-16 parameters to be tuned and the manual tuning of all the impedance values is difficult, when possible. Our study also showed that they were codependent, leading to further complications during tuning. Our proposed UCI, on the other hand, allowed the user to adjust the knee motion, which is more intuitive compared to them adjusting the impedance parameters. The multi-dimension prosthesis control was effectively handled by the autotuning algorithm. Since our new approach uses RL to find optimal high-dimension parameters and human subjects are only expected to modify the knee behavior, we believe that this approach would better aid amputee populations in adapting the prosthesis according to their preference.

C. *Future Scope*

The current study only verifies the safety and feasibility of the UCI approach using able-bodied subjects. While this study is a necessary step to validate the idea of user-preferred prosthesis control, the approach needs to be validated with transfemoral amputee populations. Ensuring a faster response to changes in profiles would further strengthen the cause-effect relationship, thereby aiding amputees in understanding the effect of different profiles and selecting the optimal profile. Therefore, autotuning algorithms with faster convergence or initial impedance parameters are to be developed.

The current control points are temporally fixed, limiting the alternate profiles that users can explore. The possibility of manipulating temporal features of the control points could help generate profiles for a broader range of tasks, including stair climbing and slope walking. Finally, understanding the biomechanical and metabolic implications of the chosen profiles would help understand the underlying mechanisms that govern the human-machine system and pave the way for adaptable robotic devices for patient-specific and patient preferred assistance.

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