A Cyber Expert System for Auto-Tuning Powered Prosthesis Impedance Control Parameters

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Abstract—Typically impedance control parameters (e.g., stiffness and damping) in powered lower limb prostheses are fine-tuned by human experts (HMEs), which is time and resource intensive. Automated tuning procedures would make powered prostheses more practical for clinical use. In this study, we developed a novel cyber expert system (CES) that encoded HME tuning decisions as computer rules to auto-tune control parameters for a powered knee (passive ankle) prosthesis. The tuning performance of CES was preliminarily quantified on two able-bodied subjects and two transfemoral amputees. After CES and HME tuning, we observed normative prosthetic knee kinematics and improved or slightly improved gait symmetry and step width within each subject. Compared to HME, the CES tuning procedure required less time and no human intervention. Hence, using CES for auto-tuning prosthetic control was a sound concept, promising to enhance the practical value of powered prosthetic legs. However, the tuning goals of CES might not fully capture those of the HME. This was because we observed that HME tuning reduced trunk sway, while CES sometimes led to slightly increased trunk motion. Additional research is still needed to identify more appropriate tuning objectives for powered prosthetic legs to improve amputees’ walking function.

Keywords—Powered prosthetic legs, Biomechanics, Gait, Expert system, Calibration, Transfemoral amputation.

LIST OF SYMBOLS

\[ k \] Stiffness
\[ \theta_F \] Equilibrium position
\[ C \] Damping coefficient
\[ \theta_p \] Prosthesis knee joint angle
\[ \dot{\theta}_p \] Prosthesis knee joint angular velocity
\[ \theta_{\text{peak}} \] Peak knee angle
\[ T_{\text{dura}} \] Gait phase duration
\[ \dot{\theta}_{\text{peak}} \] Peak angular velocity
\[ m \] Membership function value
\[ D \] Rule degree
\[ N \] Negative
\[ P \] Positive
\[ CES \] Cyber expert system
\[ HME \] Human expert
\[ CV \] Coefficient of variation
\[ DF \] Statistical degrees of freedom
\[ GRF \] Ground reaction force
\[ IC \] Impedance control
\[ IDS \] Initial double support
\[ PKP \] Powered knee prosthesis
\[ RMS \] Root-mean-square
\[ SI \] Symmetry index
\[ SS \] Single support
\[ SWE \] Swing extension
\[ SWF \] Swing flexion
\[ TDS \] Terminal double support

INTRODUCTION

Over 600,000 people in the US live with major lower limb loss, and the prevalence of limb amputation is expected to double by 2050. Many amputees rely on lower limb prostheses to regain some function of the missing limb, though their mobility, stability, and community participation remain substantially limited. Compared to traditional energetically-passive devices, modern powered knee prostheses promise to restore more natural locomotion and provide greater functionality. Most powered knee prostheses...
rely on finite state impedance control (IC), which adjusts the impedance of the knee joints based on gait phase. The desired IC parameter values in each gait phase are often fine-tuned manually and heuristically by a prosthetist, based on observations of the patient’s gait performance and feedback, until the amputee’s gait “looks good.” Manual tuning presents a serious clinical challenge since it lacks precision, is time and resource intensive, and must be conducted uniquely for each amputee to account for between-patient variation. New approaches that can configure the prosthesis control parameters quickly and cost-effectively are needed to make powered lower limb prostheses more practical for clinical use.

The two main concepts to simplify the tuning procedure have been (1) to mimic able-bodied or sound limb impedance at prosthetic joints, and (2) to reduce the number of parameters that need to be tuned. Biological joint impedances have been computed directly from experimental measurements and estimated using biomechanical models. Due to experimental limitations, in vivo joint impedance during ambulation has only been measured at the ankle during the stance portion of gait. Impedance measurements at other joints, such as the knee, were made under static or quasi-static conditions and therefore may not transfer to dynamic ambulation tasks. Impedance estimated from musculoskeletal biomechanical models has only been validated for the stance phase of gait. Given the limited availability of biological impedance data, applying it toward the control of prosthetic joints during ambulation has not yet been demonstrated.

In a finite state machine-based controller, reducing the number of control parameters that must be calibrated may be achieved by defining fewer states. However, only modest simplification can be achieved since at least 3 states are typically defined for level-ground walking, and parameter values differ across tasks (i.e., ramp ascent/descent, stair ascent/descent). Another solution to tune fewer parameters is to associate parameter values with one another or with other intrinsic biomechanical measures (e.g., gait phase and gait speed). In one case, this strategy not only reduced the burden of manual tuning, but also permitted alternate nonlinear control systems that had fewer control parameters altogether. However, given their complexity, explicit relationships between biomechanical measures and control parameters may be imprecisely known and potentially unsuitable as a basis for prosthesis control. Ultimately, parameter reduction only simplifies the tuning procedure, leaving many of the practical costs and challenges of tuning powered prostheses unsolved.

Fundamentally different from existing approaches, our new concept is to configure the impedance control parameters for powered prostheses using a cyber-expert system (CES). A branch of artificial intelligence, CESs encode human expert (HME) factual knowledge or skills into a computer system as databases and rules. HME knowledge can be represented in several ways, including a semantic network, production rules, predicate logic, object-attribute-value, hybrids, and scripts, depending on the type of knowledge and field of application. In our application, CESs tune prosthesis control parameters by qualitatively observing knee kinematics and gait characteristics (e.g., stride length and step symmetry), which involve cause-and-effect decisions that are typically represented as production rules. Additionally, since tuning decisions vary depending on the magnitude of observed, continuously varying gait characteristics, HME knowledge is best represented in a sliding scale manner using fuzzy logic, rather than traditional crisp logic.

Motivated by this new CES tuning concept, in this study we aimed to develop a rule-based CES to automatically tune the impedance control parameters for a powered knee (passive ankle) prosthesis. The CES performance was quantified on four human subjects to show the feasibility of our novel design. The developed cyber-expert system and study results may lead to a practical solution to configure powered prosthesis impedance control parameters quickly, accurately, and cost-effectively—all features that should facilitate the widespread adoption of advanced powered knee prostheses.

**MATERIALS AND METHODS**

**Prosthesis Design and Control Structure**

We used a powered knee prosthesis (PKP) prototype previously developed by our research group. The knee joint, comprised of a moment arm and pylon, was driven by a direct current motor (Maxon, Switzerland) through a ball screw (THK, Japan). Sensors were embedded in the PKP to measure knee joint angle (potentiometer), knee joint angular velocity (encoder connected with the motor), and ground reaction force (GRF) (6 degrees of freedom load cell (ATI, NC, USA) mounted in line with the shank pylon). The powered prosthesis was tethered and controlled by a desktop PC. A multi-functional data acquisition card (National Instruments, TX, USA) collected all sensor measurements at 100 Hz and provided digital-to-analog control output to drive the DC motor through a motor controller (Maxon, Switzerland). A low profile prosthetic foot (1E57 Lo Rider, Otto Bock, Germany) was used in the prototype.
Finite-state impedance control (IC) was used to control knee forces generated by the PKP during gait. The level ground walking gait cycle was divided into five states (phases): initial double support (IDS), single support (SS), terminal double support (TDS), swing flexion (SWF), and swing extension (SWE). Transitions between states were triggered by the GRF, knee joint angle, and knee joint angular velocity measured from the prosthesis. Within each state, three IC parameters, stiffness ($k$), equilibrium position ($\theta_E$), and damping coefficient ($C$), were set at constant values to modulate joint torques generated by the PKP as a function of the measured knee joint angle ($\theta_p$) and angular velocity ($\dot{\theta}_p$) during gait (Eq. 1).

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

(1)

**Experimental Protocol**

*Participants and Materials*

The experimental protocol was approved by the Institutional Review Board (IRB) of the University of North Carolina at Chapel Hill and all subjects gave their informed consent to participate. Two male able-bodied subjects (AB1 and AB2; height/weight: 181 cm/90 kg and 183 cm/93 kg, respectively) and two male unilateral traumatic transfemoral amputees (TF1 and TF2; height/weight: 182 cm/84 kg and 183 cm/100 kg, respectively) participated in this study. Three subjects (AB1, AB2, and TF1) participated in HME tuning trials and CES tuning trials; data collected during HME tuning trials were used to build the CES rule base. Subject TF2, whose data was not used to build the CES rule base, only participated in the CES tuning trials to evaluate the generalizability of the CES across amputees.

During all experiment trials, subjects walked on an instrumented treadmill at a speed of 0.6 m $s^{-1}$ to ensure that subjects could maintain a consistent gait pattern. Force plates mounted on the treadmill recorded GRFs under both feet. Intrinsic PKP mechanical measurements (i.e., prosthetic knee angle, angular velocity, and GRFs) were sampled at 100 Hz. Forty-one reflective markers were attached to the torso, pelvis, and both lower limbs, while an eight-camera motion analysis system (VICON, Oxford, UK) captured the marker positions, sampled at 100 Hz. Subjects wore a fall-arrest harness while walking to ensure their safety. All measurements were synchronized.

Before data collection, each subject was fit with our powered prosthesis. A special adaptor was made to allow able-bodied subjects to wear the prosthesis (Fig. 1). On days prior to testing, subjects trained to walk with the PKP in our lab for approximately 10 h until they felt comfortable walking at a speed of 0.6 m $s^{-1}$ without holding a railing.

**Human Expert Tuning**

In one condition, an experienced HME tuned the IC parameters of the PKP while subjects walked on a treadmill. The HME had designed the powered prosthesis and its control algorithm. Prior to this study, he had completed observational gait analysis and biomechanics courses, and independently conducted parameter tuning for twenty subjects.

Eight initial IC parameter sets in each gait phase were defined as 1 of 8 possible arrangements of the maximum and minimum values of each parameter (see Table 1) among fine-tuned parameters (unpublished

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**TABLE 1. Initial impedance control parameter extrema values.**

<table>
<thead>
<tr>
<th>IC parameters</th>
<th>Phases</th>
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<tbody>
<tr>
<td></td>
<td>IDS</td>
</tr>
<tr>
<td>Stiffness, $k$ (Nm deg$^{-1}$)</td>
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<td>High</td>
<td>2.2</td>
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<td>Low</td>
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<tr>
<td>Equilibrium position, $\theta_E$ (degrees)</td>
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<td>High</td>
<td>10</td>
</tr>
<tr>
<td>Low</td>
<td>4</td>
</tr>
<tr>
<td>Damping coefficient, $C$ (Nm deg$^{-1}$)</td>
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<td>High</td>
<td>0.1</td>
</tr>
<tr>
<td>Low</td>
<td>0.01</td>
</tr>
</tbody>
</table>

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**FIGURE 1.** Powered knee prosthesis prototype with adaptor allowing able-bodied subjects to walk with the prosthesis.
data) of previous test subjects (14 able-bodied subjects and 6 transfemoral amputees). Eight IC parameter profiles containing initial IC parameter sets for all 5 gait phases were constructed. The order of sets within each phase was randomized using a random number generator algorithm in MATLAB (The MathWorks, Inc., Natick, MA).

Subjects AB1, AB2, and TF1 completed 8 walking trials during which the HME tuned IC parameters. The order in which the eight initial IC parameter profiles were used in each trial was randomized in MATLAB, again with a random number generator algorithm. Subjects were permitted to walk for approximately 10–20 strides before tuning began. The expert qualitatively observed subjects’ gait performance (i.e., stride length, step symmetry, and trunk motion) and onboard sensor readings (i.e., PKP knee angle) from the prosthesis, and tuned IC parameters accordingly. IC parameter values on the prosthesis were then updated based on the expert’s tuning. The three procedures (observing, tuning, and updating) were conducted sequentially within each tuning cycle, which was repeated until the expert was satisfied with the prosthesis performance. In each tuning cycle, there was no limitation on how many IC parameters the expert could adjust. Subjects walked with fine-tuned IC parameters for 15 strides before the trial was stopped. To ensure that the expert tuned the parameters by observation rather than memory of previous tuning results, only incremental tuning was permitted; true IC values were not available to the expert during or after tuning.

**Cyber Expert System Design**

We designed a CES based on fuzzy logic inference that encoded a human expert’s knowledge and experience into computer rules to tune the IC parameters of a PKP (Fig. 2). IC parameters were tuned to reproduce the average knee angle trajectory of healthy adults during level ground walking, since normative gait behavior has been the target of other powered knee prostheses. Three gait parameters, computed from intrinsic prosthesis measurements, were used to characterize the knee angle trajectory in each gait phase: peak knee angle ($\theta_{\text{peak}}$), peak angular velocity ($\dot{\theta}_{\text{peak}}$), and peak angular velocity ($\ddot{\theta}_{\text{peak}}$). $\theta_{\text{peak}}$ was the maximum knee flexion angle for IDS, SWF, and SWE, and the maximum knee extension angle for SS. $\dot{\theta}_{\text{peak}}$ was the maximum flexion angular velocity for IDS, TDS, and SWF and the maximum extension angular velocity for SWE and SS.

For each gait phase (state), a fuzzy logic tuner was designed using the well-known WM approach from...
Wang and Mendel\textsuperscript{41} that has been widely used in other applications.\textsuperscript{12,22} This approach was chosen because it permits an adaptive, expandable rule base as more training data become available.\textsuperscript{7} Each fuzzy tuner consisted of a fuzzification block, rule-base, inference engine, and defuzzification block. During fuzzification, crisp inputs were converted into grades in individual membership functions that determined how inputs should be interpreted by the linguistic rules. The rule-base stored the knowledge, in the form of IF–THEN rules, of how to change outputs given a set of inputs. The inference engine determined which rule to use to map fuzzified inputs into fuzzified outputs. The defuzzification block converted the fuzzified output into crisp outputs.

The inputs of the fuzzy tuner for each gait phase were the difference (\(\Delta \theta_{\text{peak}}\), \(\Delta T_{\text{dura}}\), and \(\Delta \dot{\theta}_{\text{peak}}\)) between the prosthesis and target gait parameters averaged across five consecutive strides. The outputs were the changes in IC parameters (\(\Delta k\), \(\Delta \theta_{\text{E}}\), and \(\Delta C\)). Two trapezoid membership functions, negative (N) and positive (P), were defined for each input and output parameter, with the domain intervals of the fuzzy regions normalized by the minimum and maximum parameter values during the preliminary HME tuning experiments. Multiplication was used for the fuzzy “and” logic, while maximization was used for the “or” logic. The inference was made by clipping the output membership function at the input strength for each rule. The combination of outputs in multiple rules was achieved by fuzzy “or” logic. Crisp outputs were computed using a centroid defuzzification algorithm.\textsuperscript{41}

Key to designing the CES was building the fuzzy rule-base, established using data collected from the HME tuning trials for AB1, AB2, and TF1. For each instance when the HME adjusted the IC parameters, input–output data pairs having three inputs (\(\Delta \theta_{\text{peak}}\), \(\Delta T_{\text{dura}}\), and \(\Delta \dot{\theta}_{\text{peak}}\)) and one output (\(\Delta k\), \(\Delta \theta_{\text{E}}\), or \(\Delta C\)) were formulated and normalized by multiplying the maximum adjustment of that impedance parameter during HME tuning. Values in each input–output data pair were assigned to the membership function, either N or P, for which the projected function value, \(m\), was higher. Rules in the form of IF–THEN statements were then generated for each data pair (e.g., Eq. 2).

\begin{equation}
\text{Rule: IF } \Delta \theta_{\text{peak}} \text{ is N}, \Delta T_{\text{dura}} \text{ is N, and } \Delta \dot{\theta}_{\text{peak}} \text{ is P, THEN } \Delta \theta_{\text{E}} \text{ is P.}
\end{equation}

To resolve conflicts between rules with the same IF part but different THEN parts, a degree \(D\) was assigned for each rule (Eq. 3), and only the rule with the highest degree in the conflict group was accepted for the final rule-base.

\[
D(\text{Rule}) = m(\Delta \theta_{\text{peak}})m(\Delta T_{\text{dura}})m(\Delta \dot{\theta}_{\text{peak}})m(\Delta \theta_{\text{E}}).
\]

The final rule base (Tables A, B, C), included as Electronic Supplementary Material, contained eight rules relating inputs to each output IC parameter, or 24 rules for each gait phase.

\textit{Cyber Expert Tuning}

All four subjects participated in the CES tuning trials, conducted on different days from the previous procedures. Subjects AB1, AB2, and TF1 completed 16 walking trials (8 CES tuning, 8 non-tuning), while subject TF2 completed 8 walking trials with CES tuning only. The same eight initial IC parameter profiles and randomization procedure used in the HME tuning trials were adopted here in both the tuning and non-tuning trials. CES tuning was initiated approximately 30 s after starting the trial, and IC parameters were tuned only if specific criteria were met. To ensure that subjects had adjusted to current IC parameter values, the CES tuned impedance parameters if the variance in gait parameters (\(\theta_{\text{peak}}, T_{\text{dura}}, \theta_{\text{peak}}\)) over five consecutive strides was less than the parameter variance during walking following HME tuning. During online tuning, gait parameter errors (\(\Delta \theta_{\text{peak}}, \Delta T_{\text{dura}},\text{ and }\Delta \dot{\theta}_{\text{peak}}\)) averaged over the last 5 consecutive strides were used as CES inputs. The impedance values were updated based on the CES outputs. The CES stopped tuning when the root-mean-square (RMS) error between the prosthesis and target knee joint angles over five consecutive strides was less than 3°, or 1.5 times the joint angle standard deviation during walking in healthy adults.\textsuperscript{34} Subjects walked with fine-tuned IC parameters for 15 strides before the trial was stopped.

\textit{Data Analysis to Compare HME and CES Tuning Performance}

We computed the RMS error between the prosthesis knee motion and target knee joint angle representing normative knee kinematics during walking. We also computed common global measures of gait performance as an indicator of subjects’ overall adaptation to the prosthesis over a trial, including stance/swing duration index, step width, and trunk sway.

Stance and swing duration symmetry, common measures of general gait performance in lower limb amputees,\textsuperscript{26,40} were quantified by the symmetry index (Eq. 4), where \(S\) and \(P\) are the gait phase duration of subjects’ sound and prosthetic lower limbs, respectively.\textsuperscript{26}
\[ SI = \frac{(S - P)}{(S + P) \times 0.5} \]  

Step width, an indicator of stability, was computed as the medial–lateral distance between heel markers at heel strike.\(^{21}\) Trunk sway, another indicator of stability, was computed as the peak-to-peak distance of the T10 spinal vertebra (located with a reflective marker by motion capture) in the lateral-medial and anterior-posterior directions during a stride cycle.\(^{3}\) Trunk movement was monitored only for subjects TF1 and TF2.

As the tuning procedure progressed, we expected that symmetry index magnitude would decrease if bilateral gait timing became more symmetric; step width would decrease if subjects felt more stable;\(^{27}\) and trunk movement would decrease if subjects’ balance improved.

RMS error, symmetry index, step width, and trunk sway were computed for each stride and averaged over 10 consecutive strides at both the beginning and end of trials. For both CES and HME tuning methods, these quantified metrics were compared before and after tuning IC parameters; a one-tailed paired Student’s \(t\) test was conducted across trials within each individual subject. Additionally, we compared the quantified metrics derived after HME tuning to those derived after CES tuning using two-tailed paired Student’s \(t\) tests across subjects AB1, AB2, and TF1.

As a measure of the repeatability of CES and HME tuning, we computed the coefficient of variation (CV),\(^{13}\) the ratio of the standard deviation to the mean, in fine-tuned IC parameters for each subject and each gait phase. We further averaged the CV across phases for each subject and then compared the CV between HME and CES using two-tailed paired Student’s \(t\) tests across subjects AB1, AB2, and TF1.

For all statistical comparisons, significant differences were defined for \(p < 0.05\).

**RESULTS**

Both CES and HME tuning produced a more normative prosthetic knee angle trajectory. For both tuning methods, post-tuning RMS error decreased significantly compared to pre-tuning RMS errors in AB1, AB2, and TF1 (see statistics in Table 2). This was also observed in the CES tuning trials collected from TF2, whose data were not used to build the CES rule base (Table 2; Fig. 3). For non-tuning trials within each subject, we observed a slight, but non-significant, reduction of RMS errors at the end of the trials (Table 2), indicating that improvement in knee angle trajectory over the tuning trials was primarily due to tuning rather than to subjects’ adaptation to initial IC parameters. CES tuning yielded smaller RMS errors than HME tuning, consistently observed in AB1, AB2, and TF1. Compared to RMS errors after HME tuning averaged across subjects, RMS errors after CES tuning (Fig. 3) showed more consistent and lower values. However, the post-tuning RMS error difference between CES and HME tuning trials was not statistically significant across 3 tested subjects (\(p = 0.210, \ t = 1.82, \ DF = 2\)) (Fig. 3).

Stance and swing duration symmetry improved significantly after HME tuning for subjects AB1, AB2, and TF1 (Table 3). The gait symmetry of each tested subject also improved after CES tuning, but not all improvements were statistically significant (Table 3). There was no difference in the subjects’ post-tuning stance (\(p = 0.916, \ t = 0.12, \ DF = 2\)) or swing (\(p = 0.868, \ t = 0.19, \ DF = 2\)) duration symmetry between HME and CES tuning trials (Fig. 4).

Both HME tuning and CES tuning reduced the step width of each subject (Table 4; Fig. 5). The step width reductions were statistically significant for all subjects who participated in HME tuning, while reductions from CES tuning were significant only for subjects AB1 and TF2 (Table 4). Compared with HME, CES yielded comparable post-tuning step width averaged across 3 subjects (\(p = 0.518, \ t = 0.78, \ DF = 2\)) (Fig. 5).

The trunk sway was captured from TF1 during HME and CES tuning, and from TF2 during CES tuning only. For TF1, HME tuning significantly reduced trunk sway in the lateral–medial (\(p = 0.022, \ t = 2.45, \ DF = 7\)) and anterior–posterior (\(p = 0.007, \ t = 2.45, \ DF = 7\)).
The coefficient of variation (CV) in fine-tuned IC parameters following both HME and CES tuning, averaged across 3 subjects, was shown in Fig. 7. Comparable CV of stiffness ($k$) was observed between the two tuning methods. The CVs of damping coefficient ($C$) and equilibrium position ($\theta_E$) were higher after CES tuning than those after HME tuning, but the differences were not statistically significant.

The HME tuning procedure required the subject to take 187.7 strides (SD = 76.6), compared to only 96.2 strides (SD = 29.8) during CES tuning. HME changed IC parameters on an average of 7 times per trial (SD = 2.6), while the CES tuned IC parameters 10.3 times per trial (SD = 4.2).
DISCUSSION

Cyber Expert System (CES) is a Potentially Cost-Effective Approach for Tuning Impedance Control Parameters of Powered Prostheses

Proficient and cost-effective automatic tuning systems are needed to improve the clinical viability of modern powered prosthetic devices while enabling more natural walking ability. We developed a rule-based CES that automatically tuned the impedance control (IC) parameters of a prototype powered knee prosthesis and closely reproduced an able-bodied knee angle trajectory during level-ground walking. Compared to manual HME tuning, CES tuning can achieve comparable performance quickly without human expert intervention. Ideally, fine-tuning IC parameters with our CES only requires the amputee user to don the powered prosthesis and walk on level ground for several minutes, even outside of the clinical setting, e.g., at home. The CES might then enable the prosthesis to facilitate user adaptation over time by tuning IC parameters either continuously or periodically when initiated by the user. Therefore, our CES might reduce the number of clinical visits and, consequently, healthcare costs for lower limb amputees.

Determining the Prosthesis Control Objective is Critical

Not surprisingly, the CES tracked the normative knee trajectory more precisely than the HME by tuning based on quantitative measures rather than qualitative observation. This was observed in all 3 subjects who participated in both the CES and HME tuning trials, although the difference was not statistically significant due to the limited number of human subjects involved in this pilot evaluation. Overall, the CES tuning improved or slightly improved gait symmetry and step width in all the subjects. Additionally, the repeatability of CES tuning was comparable to that of HME tuning. However, trunk sway was not reduced after CES tuning as it was following HME tuning, indicating that the human expert’s tuning goals may extend beyond the CES’s goal of reproducing normative knee joint kinematics. This implication might also be reflected through the relative disagreement between HME and CES fine-tuned IC parameters (Fig. 8).

Furthermore, though joint kinematics and impedance of able-bodied subjects have been the target of other powered prosthesis controllers, the additional socket-limb interface, joint mechanics, and segment

**FIGURE 6.** Mean (±SD) trunk sway before and after tuning. Trunk sway was only measured for subjects TF1 and TF2. TF2 only participated in CES tuning procedure. Hence, the results were averaged across eight trials of each tuning method for each subject. * denotes statistical significance ($p < 0.05$).

**FIGURE 7.** Mean (±SD) coefficient of variation (CV) of fine-tuned IC parameters following HME and CES tuning. The results were averaged across the three tuned gait phases, then averaged across three subjects (AB1, AB2, and TF1).
inertial and geometric properties of current PKPs do not match those of a biological lower limb. Therefore, imposing biological kinematic and dynamic constraints on a non-biological mechanical system may not necessarily elicit natural and optimal gait performance.

A critical question that now remains is: What is the optimal control objective for a powered lower limb prosthesis to maximize user performance? Based on tuning results derived from both HME and CES, the fine-tuned IC parameters varied over a range of values, meaning multiple joint impedance values all satisfied the human/cyber expert’s tuning criteria. Consequently, there may be no unique optimum parameter solution, and reproducing gait that simply “looks good” might be attainable over a wide range of fine-tuned parameter values. More important optimization criteria may focus on the user’s walking function (e.g., walking stability, symmetry, metabolic effort, ability of the human–machine system to reject perturbations) and overall satisfaction. Additional studies are needed to identify more appropriate neural, mechanical, and energetic targets to guide the design, evaluation, and optimization of powered lower limb prostheses. Such performance targets would ideally account for the unique mechanical characteristics of the human-prosthesis system, restore the user’s locomotion function, and receive higher user acceptance.

Sensitivity of the User’s Performance to IC Parameters is Needed

Though all subjects achieved near normal knee kinematics after tuning, the human expert did not tune IC parameters during the terminal double support (TDS) and swing flexion (SWF) phases. Therefore, the CES likewise did not tune IC parameters during the TDS and SWF phases. The human expert reported difficulty in qualitatively evaluating knee kinematics and walking performance during these phases and, thus, in knowing how to change the IC parameters. In preliminary studies (not published) in our lab, gait parameters during the TDS and SWF phases show little sensitivity to changes in IC parameters within the range of fine-tuned IC parameter values from previous subjects, suggesting that IC parameter tuning may not be necessary during these phases. Future studies are needed to characterize the sensitivity of gait performance to changes in IC parameters and better define the tuning requirements within the CES.

Limitations of CES Approach

Compared to previous concepts to impose biological joint impedance or incorporate fewer tuned parameters, our CES has proven easy to implement, has shown promising results in this study, and can be directly applied to patients with lower limb amputations. However, the CES has several limitations. First, the CES rule base may have been biased or incomplete since it was founded heavily on the knowledge and experiences of one human expert. Building a CES based on the knowledge of more experts might further improve the performance of the auto-tuning system for prosthesis control. As mentioned previously, additional or different tuning goals may yield better global gait performance but may require more sensors, leading to other design (electronic components for sensing and communication) and practical (donning extra components on the body) challenges. Apart from our expert system approach, formal optimization methods such as “shooting” or “gradient descent” may effectively tune IC parameters without requiring empirical data.

The CES only tuned about half of all configurable parameters in the prosthesis controller (i.e., the low-level IC parameters with each state). Other parameters that could be tuned include those that define transition rules between states, including ground reaction force.
thresholds distinguishing swing and stance phases, and knee angles and angular velocities distinguishing phases within swing and stance. Future studies should explore whether tuning parameters related to the finite-state transition rules further improves gait performance.

**Limitation of this Study**

One limitation of this study was that we only evaluated 3 measures of gait performance: temporal symmetry, stance width, and trunk sway. Better criteria for evaluating and rating PKP gait performance, including measures that reflect global human–prosthesis interaction effects, are needed (e.g., lower limb joint mechanical power distribution, metabolic cost). Another limitation was that only four human subjects were involved in this study to demonstrate the feasibility of CES. The limited sample size constrained the statistical analysis power. In addition, we only tested one transfemoral amputee subject whose data was not used to build the fuzzy rule base in the CES, so it is unclear whether the CES rule base is generalizable across the amputee population; more subjects need to be tested. Finally, in this study, we only demonstrated a CES design based on fuzzy logic inference. Other adaptive structures, such as case-based reasoning or neural network, might be worth exploring in future CES designs since they permit the expert system to learn from previous successful examples rather than rely on a fixed rule-base.

The CES only tuned IC parameters for a single actuated joint (knee). In contrast, prostheses with powered knee and ankle joints may enable more natural walking but present an even greater tuning challenge that would greatly benefit from a CES. It remains to be seen whether human manual tuning proficiency is sufficient to build an effective CES for multi-powered-joint prostheses.

**Conclusions**

In conclusion, we developed a cyber expert system (CES) that uses fuzzy logic inference methods to effectively tune the impedance control parameters of a powered knee prosthesis (PKP) during level-ground walking. While restoring normative knee kinematics generally improved subjects' overall gait performance, greater gains may be achieved by considering additional neural, biomechanical, or energetics measurements in the tuning decisions made by the CES. Given its effectiveness and potential generalizability, the CES is potentially a powerful clinical tool that could make PKPs more practical and accessible for widespread use.

**ELECTRONIC SUPPLEMENTARY MATERIAL**

The online version of this article (doi:10.1007/s10439-015-1464-7) contains supplementary material, which is available to authorized users.

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**CONFLICT OF INTEREST**

No benefits in any form have been or will be received from a commercial party related directly or indirectly to the subject of this manuscript.

**REFERENCES**

Auto-Tuning Powered Prosthesis Control Parameters


