Adaptive Control of Powered Transfemoral Prostheses Based on Adaptive Dynamic Programming*

Yue Wen, Ming Liu, Jennie Si, *Fellow, IEEE* and He (Helen) Huang, *Senior Member, IEEE*

Abstract— **In this study, we developed and tested a novel adaptive controller for powered transfemoral prostheses. Adaptive dynamic programming (ADP) was implemented within the prosthesis control to complement the existing finite state impedance control (FS-IC) in a prototypic active-transfemoral prosthesis (ATP). The ADP controller interacts with the human user-prosthesis system, observes the prosthesis user's dynamic states during walking, and learns to personalize user performance properties via online adaptation to meet the individual user's objectives. The new ADP controller was preliminarily tested on one able-bodied subject walking on a treadmill. The test objective was for the user to approach normative knee kinematics by tuning the FS-IC impedance parameters via ADP. The results showed the ADP was able to adjust the prosthesis controller to generate the desired normative knee kinematics within 10 minutes. In the meantime, the FS-IC impedance parameters converged at the end of the adaptive tuning procedure while maintaining the desired human-prosthesis performance. This study demonstrated the feasibility of ADP for adaptive control of a powered lower limb prosthesis. Future research efforts will address several important issues in order to validate the system on amputees. To achieve this goal, human user-centered performance objective functions will be developed, tested, and used in this adaptive controller design.**

I. INTRODUCTION

Powered lower limb prostheses have enabled lower limb amputees to walk more naturally and efficiently [1]–[3]. Some of these advanced devices have become commercially available (e.g., BiOM ankle, BionX Medical Technologies, Inc.). Most of these devices use a finite-state machine (FSM) to adjust the impedance of prosthetic joints since humans reportedly control the stiffness of leg muscles, and therefore joint impedance, while walking [4]–[6].

However, the practical value of these devices is limited because the prosthesis control parameters (e.g., joint impedance) must be customized for individual users manually, and there is no effective way to determine these control parameters. Currently, the control parameters are manually and heuristically tuned by prosthetists in clinics for each locomotor task. The parameters stay fixed outside of the clinics. This approach presents two critical barriers: 1) it increases the cost for amputees to use powered devices because the manual tuning procedure is time- and labor-intensive, and 2) the device cannot adapt to variability in user behavior (e.g., gait pattern) and real-life environments (e.g., load carriage). To cope with more long-term user variations, additional clinic visits might be needed to readjust the prosthesis control. To deal with immediate environment changes, the user must use additional strategies to compensate for inadequate assistance from the prosthesis. Clearly, adaptive control is needed to enhance the function and practical value of powered artificial legs.

On account of user variability, previous research efforts have attempted to customize the prosthesis control parameters to individual users. One approach is to configure sound-limb impedance for prosthesis control. Biological joint impedance has been computed directly from experimental measurements of able-bodied persons [7] or estimated using biomechanical models [8]. However, applying biological impedance data to prosthetic joints as a means of control during ambulation has not yet been demonstrated. Another approach is to relate joint impedance values with mechanical measurements sensed by prosthesis intrinsic sensors. For instance, control parameters have been defined as a function of prosthesis joint angles, prosthesis load, foot center of pressure, and effective leg shape [9]–[11]. These measurements of biomechanical parameters can then be used to estimate joint impedance. This approach is useful not only for customizing prosthesis control parameters, but also for online adaptive control. However, given their complexity, explicit relationships between biomechanical measures and control parameters may be imprecise and unsuitable as a basis for prosthesis control. Another existing concept is to heuristically and automatically tune the prosthesis control parameters toward desired performance objectives. Our group designed a cyber expert system that mimics human experts' tuning decisions [12]. The major barrier of this approach is that the cyber expert system performance heavily depends on the knowledge of human experts.

* This work was partly supported by NSF #1406750 and #1361549.

Y. Wen, M. Liu, and H. Huang are with the NCSU/UNC Department of Biomedical Engineering, NC State University, Raleigh, NC, 27695-7115; University of North Carolina at Chapel Hill, Chapel Hill, NC 27599.

J. Si is with the Department of Electrical, Computer, and Energy Engineering, Arizona State University, Tempe, AZ, 85281.

Corresponding author: Yue Wen (E-mail: ywen3@ncsu.edu, Phone number: 919-515-8541).

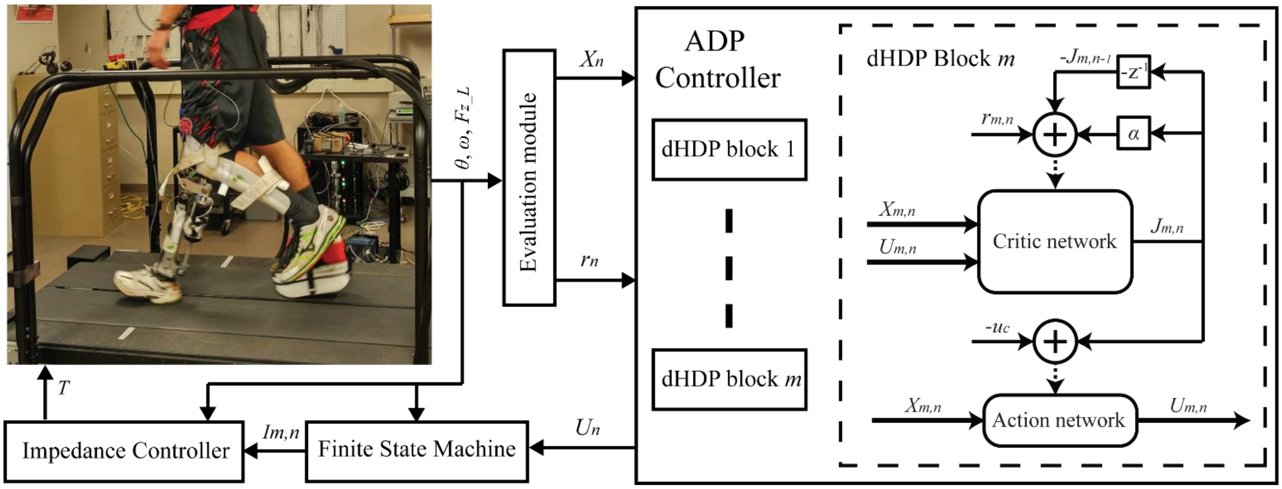

Figure 1. The structure of the human-in-the-loop ADP tuner. This structure has three hierarchical loops: 1) the inner loop is an impedance controlling algorithm running at a frequency of 100*Hz*; 2) the middle loop is finite state machine strategy periodically shifting state along a gait cycle; 3) the outer loop is ADP tuning iteration happening every five gait cycles.

Motivated by the needs for adaptive control of powered lower limb prostheses, we propose a novel adaptive prosthesis control design approach based on adaptive dynamic programming (ADP) [13]. ADP is used as a supplementary controller to the existing finite state impedance control (FS-IC) for powered prostheses. The ADP controller learns to improve the performance of the human user by observing the human-prosthesis system and providing online adaptation. This is drastically different from the expert system approach that computerizes human expert knowledge; instead, ADP uses reinforcement learning and approximation methods to automatically and optimally find powered prosthesis limb control parameters.

The purpose of this preliminary study was to test our recently developed ADP-based controller performance as it automatically configures prosthesis control parameters. The controller was implemented in our prototypic active-transfemoral prosthesis (ATP) [14], [15]. The system was evaluated on one able-bodied subject, walking with the powered prosthesis on a treadmill. Our results demonstrated the feasibility of our novel approach for adaptive and optimal control of powered lower limb prostheses.

II. Methodology

A. Finite State Impedance Controller

The ATP was regulated by FS-IC to mimic periodic movement of a human knee. The finite state machine consisted of five states, corresponding to five gait phases that are often defined in clinics: initial double support (IDS), single support (SS), terminal double support (TDS), swing flexion (SWF), and swing extension (SWE). Within a given phase, a set of specific impedance parameters (i.e., stiffness (K), damping (B), and equilibrium position (θe)) defined the dynamics of the ATP. The impedance controller took current position (θ) and current velocity (ω) as inputs and output the reacting torque (T) as:

$$T = \mathrm{K}(\theta - \theta e) + \mathrm{B}\omega. \quad (1)$$

B. Human-prosthesis Evaluation Module

The ADP controller adjusts prosthesis control based on human-prosthesis performance. This module evaluates the performance by quantifying the errors between ADP objective (tuning target) and actual human-prosthesis performance.

1) ADP Objective

In this study, the tuning objective for prosthesis impedance control was to produce normative knee kinematics in walking. This objective has been previously used to evaluate the powered prosthetic knees [1], [2], [11]. Knee kinematics in one gait cycle were represented by eight features: duration time (D_m) and peak angle (P_m) in stance flexion, stance extension, swing flexion, and swing extension, where *m* is the gait phase index. We used a previously published normative knee profile [16] to determine the target features, denoted as D_m^t and P_m^t.

2) State of Human-prosthesis Systems

The state of the human-prosthesis system ($X_{m,n}$) was defined by the errors between the target features described above and the actual ATP motion ($\Delta P_{m,n}, \Delta D_{m,n}$) and the first order derivative of these errors ($\Delta P'_{m,n}, \Delta D'_{m,n}$). Here, *m* denotes the gait phase index, and *n* denotes the tuning iteration number.

3) Reinforcement Signal r_n

We defined an instantaneous evaluation criteria to assess the interaction between the ADP controller and human-prosthesis system and provide feedback to the ADP tuner for reinforcement learning. A failure reinforcement signal was given when the $\Delta P_{m,n}$ and/or $\Delta D_{m,n}$ exceeded predefined limitations. FS-IC was reset to its initial impedance parameters to avoid potential safety threats to the prosthesis user. In addition, a penalty reinforcement signal was given when the performance of human-prosthesis system deteriorated as measured by an increase in $|\Delta P_{m,n}|$ and/or $|\Delta D_{m,n}|$.

C. ADP-based Controller Implementation

We implemented an ADP-based controller using a modified direct heuristic dynamic programming (dHDP) method [17] to tune the impedance parameters of FS-IC. The ADP-based controller took the state of human-prosthesis system (X_n) and reinforcement signal (r_n) at the n^{th} tuning iteration as the inputs, and sent out control (U_n) to update the impedance parameter set of the FS-IC. Inside the ADP controller, one dHDP block was designated to each phase in FS-IC. In the m^{th} phase, the control output $U_{m,n}$ of the ADP controller was used to update the impedance parameters $I_{m,n+1}$ in the FS-IC.

$$I_{m,(n+1)} = I_{m,n} + \beta_{m,n} * U_{m,n}, \tag{2}$$

where $\beta_{m,n}$ is a scaling factor.

The dHDP design consisted of an action neural network and a critic neural network.

1) Action Neural Network

The action neural network consisted of three layers of neurons (4-7-3), which took in the state of human-prosthesis system and output the control to regulate it. Furthermore, the relation between input X and output U was represented by (3), where φ is a sigmoidal activation function, and W_{A2} and W_{A1} are weight matrices.

$$U = \varphi(W_{A2}\varphi(W_{A1}X)) \tag{3}$$

2) Critic Neural Network

The critic neural network also included three layers of neurons (7-7-1), which took the state X and the control U as inputs and predicted the total cost-to-go J.

$$J = W_{C2}\varphi(W_{C1}[X;U]) \tag{4}$$

The reinforcement signal $r_{m,n}$, predicted total cost-to-go $J_{m,n}$, and previous total cost-to-go $J_{m,n-1}$ were used to update both the action network and critic network as shown in Fig. 1. Details regarding the reinforcement learning algorithm may be found in a previous publication by J. Si [17].

D. ADP Evaluation

1) Experiments and Data Collection

This study was approved by the Institutional Review Board at the University of North Carolina at Chapel Hill and written informed consent was obtained by the subject. One able-bodied subject was recruited for this preliminary evaluation. An 'L' shape brace was used to allow the able-bodied subject to walk with the ATP (Fig. 1).

The subject was trained to walk with the ATP for approximately 10 hours prior to the experiment until he became accustomed to walking on a treadmill at a speed of 0.6 ms^{-1}. Prior to the experiment, the subject was equipped with a fall-arrest harness and encouraged to avoid holding the railing. The weight matrices of the ADP controller were randomly initialized in the range of [-1, 1], representing naive networks.

At the beginning, the FS-IC was assigned a set of randomly selected initial impedance parameters, which allowed the able-bodied subject to walk safely with the ATP. After the subject warmed up for one minute, the ADP controller began to tune the dynamic properties of the ATP (i.e., the impedance parameters of the FS-IC). Parameter tuning took place every five gait cycles to account for human variability while the able-bodied subject walked on the treadmill. The new impedance parameters were assigned to the FS-IC at the beginning of swing flexion phase. The tuning procedure terminated after 10 minutes.

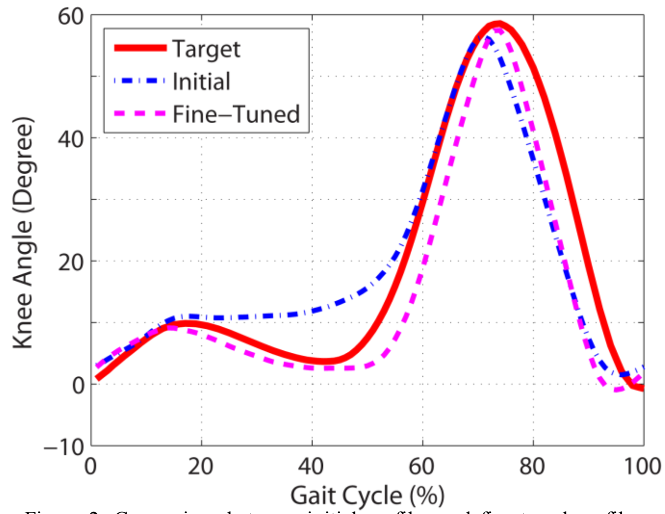

Figure 2. Comparison between initial profiles and fine-tuned profiles. The red solid line is the target profile; the blue dash-dot line is the initial ATP profile; the magenta dashed line is the fine-tuned ATP profiles. The ATP profile is the mean profile of 5 consecutive gait profiles from ATP.

Intrinsic measurements of prosthetic knee motion and ATP control signals during ADP-tuning were recorded at 100Hz.

2) Evaluation Criteria

The ADP controller was evaluated based on the following three criteria: 1) comparison between the initial, ADP-tuned, and target prosthetic knee profile to assess the overall tuning effect of ADP controller on the human-prosthesis system, 2) angle error and duration error $(\Delta D_m, \Delta P_m)$ trends to evaluate the ADP tuning effect on these dominant features, and 3) trends of the FS-IC impedance parameters (I_m) to identify if ADP controller converged. A well-learned ADP should be able to drive the ATP knee profile close to the target normative profile, maintain a good performance with small ΔP_m and ΔD_m, and obtain a set of converged impedance parameters.

III. Results

Fig. 2 shows the average ADP-tuned prosthetic knee motion in one gait cycle. ADP-tuned knee motion is much improved from the initial profile and nearly matches the target knee profile. The angle error ΔP_m and the duration error ΔD_m decreased during tuning procedure. For example, the angle error and duration error in stance extension is shown in Fig. 3. Decreased errors were observed as tuning progressed. Clearly, both angle error and duration error oscillated around 0, which meant the prosthetic knee angle feature matched the target feature and then stabilized.

Meanwhile, the FS-IC impedance parameters stabilized at the end of the tuning procedure. Fig. 4 shows the representative data in stance extension. At the sixth tuning

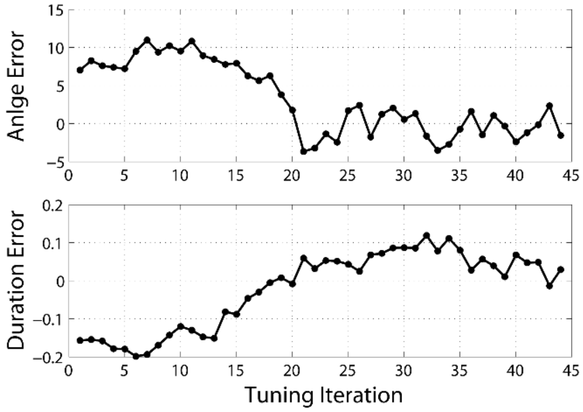

Figure 3. Resulting curves of the angle error and duration error along tuning iterations.

iteration, all three parameters reversed directions (i.e., stiffness and damping coefficients decreased and the equilibrium angle increased), which was consistent with the trends in ΔP_m and ΔD_m. All three parameters converged to a stable value at the end of the tuning procedure.

IV. Discussion

This study demonstrated the feasibility of ADP for adaptive control of active-transfemoral prostheses. An ADP-based controller trained from a naïve state was capable of acquiring cause-effect knowledge through exploration and interaction with the human-prosthesis system. The ADP-controller successfully tuned the FS-IC parameters of the ATP to approach a given objective, in our case a normative knee motion in walking, without human intervention. Both the FS-IC parameters and the human-prosthesis knee profile converged and stabilized at the end of the tuning procedure.

Results from the current study are promising yet preliminary. Only one able-bodied subject with one initial FS-IC condition was validated. Our method needs to be applied to amputees with a variety of initial conditions to validate the general capability of this ADP-based controller. Also, the reusability of the acquired knowledge was so important that we need to validate the well-learned ADP-based controller across different initial conditions and subjects. Moreover, we set the walking speed at 6 ms^{-1} during the experiment. A good auto-configuration algorithm should be able to handle different walking speeds, which will be tested in the next phase of our research. Finally, since an ideal target knee profile is difficult or may be impossible to obtain for an amputee, we need to explore more comprehensive evaluation criteria, such as stability, symmetry, and balance as tuning objectives.

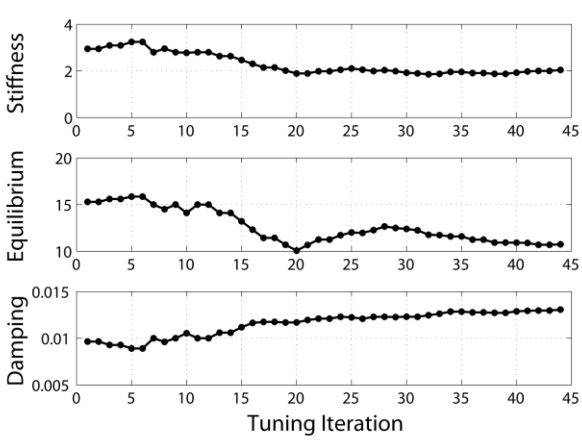

Figure 4. Changing curves of the impedance parameters along tuning iterations.

Acknowledgment

The authors thank Andrea Brandt and Stephanie Huang at North Carolina State University for their valuable suggestions for the design and assistance for the experiment.

References

[1] E. C. Martinez-Villalpando and H. Herr, "Agonist-antagonist active knee prosthesis: a preliminary study in level-ground walking," *J. Rehabil. Res. Dev.*, vol. 46, no. 3, pp. 361–373, 2009.

[2] F. Sup, H. A. Varol, J. Mitchell, T. J. Withrow, and M. Goldfarb, "Preliminary evaluations of a self-contained anthropomorphic transfemoral prosthesis," *IEEE/ASME Trans. Mechatronics*, vol. 14, no. 6, pp. 667–676, Dec. 2009.

[3] S. Au, M. Berniker, and H. Herr, "Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits," *Neural Netw.*, vol. 21, no. 4, pp. 654–666, Mar. 2008.

[4] C. T. Leonard, "The neurophysiology of human locomotion," in *Gait Analysis: Theory and Application*, Illustrate., R. L. Craik and C. A. Oatis, Eds. Mosby, 1995.

[5] N. Hogan, "Impedance Control: An Approach to Manipulation: Part II - Implementation," *Trans. ASME*, vol. 107, pp. 8–16, Mar. 1985.

[6] G. Taga, Y. Yamaguehi, and H. Shimizu, "Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment," *Biol. Cybern.*, vol. 65, pp. 147–159, Apr. 1991.

[7] E. J. Rouse, L. J. Hargrove, E. J. Perreault, and T. A. Kuiken, "Estimation of human ankle impedance during the stance phase of walking," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 870–878, Jul. 2014.

[8] S. Pfeifer, R. Riener, and H. Vallery, "Knee stiffness estimation in physiological gait," *2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Chicago, IL, 2014, pp. 1607–1610.

[9] R. D. Gregg, T. Lenzi, N. P. Fey, L. J. Hargrove, and J. W. Sensinger, "Experimental effective shape control of a powered transfemoral prosthesis," in *IEEE Int. Conf. Rehabil. Robot.*, Seattle, WA, 2013, pp. 1–7.

[10] H. Herr and A. Wilkenfeld, "User-adaptive control of a magnetorheological prosthetic knee," *Ind. Rob.*, vol. 30, no. 1, pp. 42–55, 2003.

[11] A. M. Simon, K. a. Ingraham, N. P. Fey, S. B. Finucane, R. D. Lipschutz, A. J. Young, and L. J. Hargrove, "Configuring a powered knee and ankle prosthesis for transfemoral amputees within five specific ambulation modes," *PLoS One*, vol. 9, no. 6, p. e99387, 2014.

[12] H. Huang, D. L. Crouch, M. Liu, G. S. Sawicki, D. Wang, M. Liu, G. S. Sawicki, and H. Huang, "A Cyber Expert System for Auto-Tuning Powered Prosthesis Impedance Control Parameters," *Ann. Biomed. Eng.*, pp. 1–12, Sep. 2015.

[13] J. Si, A. G. Barto, W. B. Powell, and D. Wunsch, *Handbook of learning and approximate dynamic programming*. Piscataway, NJ: John Wiley & Sons, 2004.

[14] M. Liu, P. Datseris, and H. H. Huang, "A Prototype for Smart Prosthetic Legs-Analysis and Mechanical Design," *Adv. Mat. Res.*, vol. 403–408, pp. 1999–2006, Mar. 2011.

[15] M. Liu, F. Zhang, P. Datseris, and H. Huang, "Improving Finite State Impedance Control of Active-Transfemoral Prosthesis Using Dempster-Shafer Based State Transition Rules," *J. Intell. Robot. Syst.*, vol. 76, no. 3, pp. 461–474, Dec. 2014.

[16] M. P. Kadaba, H. K. Ramakrishnan, and M. E. Wootten, "Measurement of lower extremity kinematics during level walking," *J. Orthop. Res.*, vol. 8, no. 3, pp. 383–392, May 1990.

[17] J. Si and Y. Wang, "On-Line Learning Control by Association and Reinforcement," *IEEE Trans. Neural Netw.*, vol. 12, no. 2, pp. 264–276, Mar. 2001.