

# Robot Controllers Compatible with Human Beam Balancing Behavior\*

Jongwoo Lee<sup>1</sup>, Meghan E. Huber<sup>1</sup>, *Member, IEEE*, Dagmar Sternad<sup>2</sup>, Neville Hogan<sup>1,3</sup>, *Member, IEEE*

**Abstract**—Standing on a beam is a challenging motor skill that requires the regulation of upright balance and stability. In this paper, we analyzed the behavior of humans balancing on a narrow beam without footwear. The results revealed high anti-correlation between lumped upper- and lower-body angular momentum. Despite differences in gross measures of balance, interlimb coordination was consistent between the novice and expert subjects, suggesting that both performances could be described with the same balance controller. By simulating a double inverted pendulum model utilizing different balancing controllers described in the robotics literature, we identified that the whole behavior observed from humans standing on a beam was best replicated with controllers that predominantly utilized hip actuation.

## I. INTRODUCTION

Despite low bandwidth and long latencies in the neuromuscular system, humans have a remarkable ability to maintain balance across a variety of terrains and conditions. When humans lose this ability, either due to age [1] or injury [2], it has a profound impact on their quality of life. The use of robotic exoskeletal devices is one promising approach to either replace, assist, or retrain balance, but how best to control these robotic devices to assist or retrain impaired balance ability remains a critical, open question [3].

Assisting or retraining an impaired motor behavior requires a fundamental understanding how the impaired behavior differs from the typical behavior. Without this basic knowledge, deriving successful, evidence-based interventions to provide assistance, enhance motor learning, relearning and recovery for impaired patients is problematic [4], [5].

Recent results suggest that our understanding of how healthy humans control mediolateral balance may not yet be sufficient to deliver effective robotic assistance. Domingo and Ferris attempted to enhance learning of a balance beam walking task by providing physical assistance [6] and augmenting error [7]. Counter to their predictions, practice with these interventions led to *worse* performance compared to practicing without any assistance in a beam walking task [6], [7]. This was surprising as robotic guidance and error augmentation

\*This work was supported in part by a Samsung scholarship awarded to J.L., by NIH-R01-HD087089, R01-HD081346, NSF-NRI 1637854, NSF-EAGER-1548514, and NSF-CRCNS-1723998 grants awarded to D.S., and by the Eric P. and Evelyn E. Newman fund and NIH-R01-HD087089, NSF-NRI 1637824, NSF-EAGER-1548501, and NSF-CRCNS-1724135 awarded to N.H.

<sup>1</sup>Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA

<sup>2</sup>Departments of Biology, Electrical and Computer Engineering, and Physics, Northeastern University, Boston, MA, USA

<sup>3</sup>Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA

Email addresses: jw127@mit.edu, mehuber@mit.edu, dagmar@neu.edu, neville@mit.edu

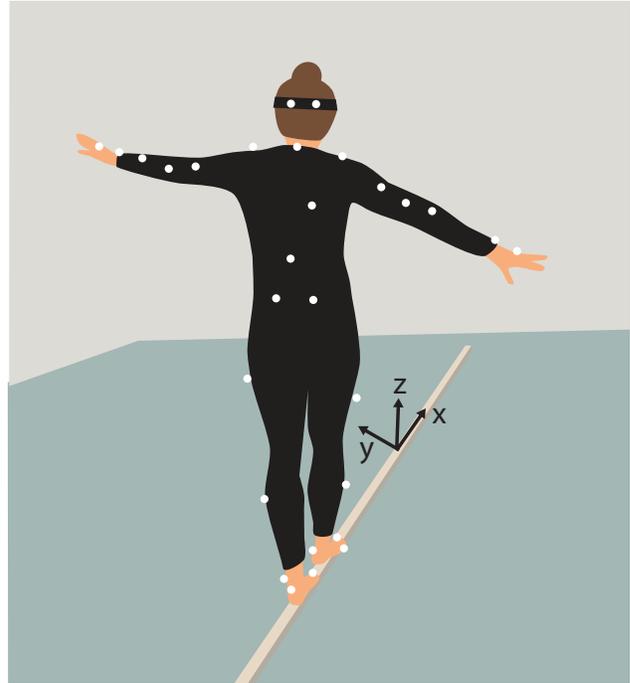


Fig. 1. Experimental Task. Subjects were instructed to maintain balance on a narrow beam (3.4cm) for as long as possible without stepping off the beam.

have previously been shown to enhance learning of a variety of other motor skills [8], [9]. One possible explanation for these unexpected results is that the interventions did not lead subjects to adopt the desired balance behavior. This begs the question, what is the desired behavior a robotic device should guide humans towards during mediolateral balance?

Walking and standing on a narrow beam, or even simply with feet in tandem, is challenging. Compared to normal stance, humans are less stable in the mediolateral direction under these conditions due to the reduced base of support [10]. Hence, balance beam standing and walking are ideal paradigms to study how balance ability can be improved using healthy subjects.

Sawers et al. previously showed that when walking on a beam, experts (trained ballet dancers) use more muscle synergies or modules compared to novices, suggesting that experts have finer coordination [11]. Unfortunately, the use of additional sensors to assess muscle activity can make an exoskeleton prohibitively difficult for the typical user to wear, calibrate, and use. Hence, describing the desired balance behavior in terms of muscle activation patterns may not be practical to provide robotic assistance or rehabilitation.

In this regard, the purpose of the present study was to identify a competent model of human balance to inform the development of exoskeleton controllers for enhancing and retraining balance. First, we examined the interlimb coordination of two subjects as they stood on a narrow beam. Specifically, we examined the spatio-temporal patterns in the angular momenta generated by individual body segments as subjects maintained mediolateral balance. To truly capture whole body coordination, we did not restrict arm movements as in the aforementioned beam walking experiments [6], [7], [11]. The two subjects included in our study consisted of a novice and an expert (i.e., trained gymnast). Thus, we also assessed whether these patterns differed with skill level.

We next examined whether existing balance controllers used in robotics could adequately describe the correlation in the angular momentum from upper and lower body observed in the human experiment. Ultimately, our results identified a subset of robotic balance controllers that could sufficiently describe both novice and expert human balance behavior. These findings provide a theoretical basis for designing exoskeleton controllers to enhance mediolateral balance of impaired or even healthy individuals.

The remainder of the paper is organized as follows. Section II examines how an expert and a novice maintain mediolateral balance when standing on a narrow beam with feet in tandem. Section III describes a subset of balance controllers currently used in robotics research. Section IV simulates the controllers described in Section III on a double inverted pendulum model and compares the simulated behavior to the human behavior reported in Section II. Section V discusses our interpretation of the experimental and simulation results, as well as their important implications for controlling robotic exoskeletons to assist or retrain mediolateral balance.

## II. HUMAN BALANCING EXPERIMENT

The purpose of this experiment was to characterize how humans with different skill levels coordinate their entire body to maintain mediolateral balance on a narrow beam. We expected that the experienced subject would have better mediolateral balance compared to the novice subject. We further predicted that the novice and expert would exhibit differences in interlimb coordination, reflecting the use of different control strategies to maintain balance in this challenging task.

### A. Methods

1) *Subjects*: We recruited two subjects to perform the balance beam task. Subject 1 (28yo old male, 180cm height, 80kg weight) was considered a novice as he did not have any formal balance training. Subject 2 (26yo female, 163cm height, 58kg weight) was a trained gymnast. The experiment conformed to the Declaration of Helsinki, and written informed consent was obtained from all subjects according to the protocol approved by the ethical committee at the Medical Department of the Eberhard-Karls-Universität of Tübingen, Germany where the experiment was conducted.

TABLE I  
SEGMENTS OF HUMAN RIGID BODY MODEL

Segment Number, $i$	Segment Name	Body Region
1	Head	Upper
2	Thorax/Abdomen	Upper
3	Right Upper Arm	Upper
4	Right Forearm	Upper
5	Right Hand	Upper
6	Left Upper Arm	Upper
7	Left Forearm	Upper
8	Left Hand	Upper
9	Pelvis	Lower
10	Right Thigh	Lower
11	Right Shank	Lower
12	Right Foot	Lower
13	Left Thigh	Lower
14	Left Shank	Lower
15	Left Foot	Lower

2) *Experimental procedure*: Each subject performed one trial in which they were instructed to stand on a narrow beam (3.4 cm width) for as long as possible with their feet in tandem (Fig. 1). Immediately prior to this experiment, both subjects performed 20 trials of balance beam walking as described in [12]. Thus, they had sufficient familiarization with the task. Subjects performed this experimental task without footwear. At the beginning of the trial, subjects placed their left (front) foot on the beam. The trial started when subjects subsequently placed their back (right) foot on the beam and ended when one foot touched the ground.

3) *Kinematic data recording and processing*: Kinematic data was collected using a 10-camera Vicon motion capture system (Oxford, UK) at a sampling rate of 100Hz. As illustrated in Fig. 1, the  $x$ -axis of the lab coordinate frame was aligned with the beam. Reflective markers were placed on the subjects' bodies following Vicon's Plug-In Gait marker set (Fig. 1). For each subject, the Plug-In Gait model, which consists of 15 rigid body segments, was fit to the kinematic data using Vicon Nexus and C-Motion Visual3D (Germantown, MD) software (see Table 1 for list of body segments). Measurements of whole body center of mass position and velocity, as well as the variables used to calculate the angular momenta of the individual body segments were computed in Visual3D. For the subsequent analyses, data from the first and the last 20% of each trial were omitted to avoid any possible transients or fatigue effects.

4) *Dependent measures*: Trial time (i.e., how long each subject could maintain balance on the beam) served as the primary measure of balance performance. The root-mean-square (RMS) of the whole body center of mass (CoM) position (with respect to the center of the beam) and velocity in the mediolateral, or  $y$  direction, were also calculated to characterize general balance ability.

To describe the full behavior of the body, we calculated the angular momentum with respect to the beam rather than the body's center of mass, which we anticipated would move considerably during the experiment [12]. The angular

TABLE II  
ANALYSIS OF HUMAN BALANCE PERFORMANCE

	Subject 1 (Novice)	Subject 2 (Expert)
Trial time [s]	23.3	421.2
RMS CoM position [cm]	1.06	0.69
RMS CoM velocity [cm/s]	0.017	0.015
Xcorr between $L_{ub}$ and $L_{lb}$	-0.95	-0.91
RMS of $L_{ub}$ [kg·m <sup>2</sup> /s]	5.54	2.00
RMS of $L_{lb}$ [kg·m <sup>2</sup> /s]	1.58	0.70
RMS of $L_{wb}$ [kg·m <sup>2</sup> /s]	4.07	1.43

momentum of  $i$ -th body segment about the axis of the balance beam (i.e., the  $x$ -axis) at each time  $t$ ,  $L_i(t)$ , was calculated by

$$L_i(t) = m_i(r_{y,i}(t)v_{z,i}(t) - r_{z,i}(t)v_{y,i}(t)) + j_{x,i}\omega_i(t) \quad (1)$$

where

- $r_{y,i}$  and  $r_{z,i}$  are the positions of the  $i$ -th segment's center of mass in  $y$  and  $z$  direction, respectively,
- $m_i$  is the mass of the  $i$ -th segment,
- $v_{y,i}$  and  $v_{z,i}$  are the linear velocities of the  $i$ -th segment's center of mass in  $y$  and  $z$  direction, respectively,
- $j_{x,i}\omega_i$  is the  $x$  component of the angular momentum of the  $i$ -th segment about its center of mass in the lab coordinate frame.

The total angular momentum of all upper body segments about beam axis at each time  $t$ ,  $L_{ub}(t)$  was calculated by

$$L_{ub}(t) = \sum_{i=1}^8 L_i(t). \quad (2)$$

The total angular momentum of all lower body segments about beam axis at each time  $t$ ,  $L_{lb}(t)$  was calculated by

$$L_{lb}(t) = \sum_{i=9}^{15} L_i(t). \quad (3)$$

The total angular momentum of the whole body (i.e., of all body segments) about beam axis at each time  $t$ ,  $L_{wb}(t)$  was calculated by

$$L_{wb}(t) = \sum_{i=1}^{15} L_i(t). \quad (4)$$

Cross-correlation analysis was conducted to assess patterns between the angular momentum generated from the different body segments.

Lastly, the external torque about  $x$ -axis at the foot-beam interaction point was estimated by

$$\tau_{ext}(t) = \dot{L}_{wb}(t) + mgr_y(t) \quad (5)$$

where  $m = \sum_{i=1}^{15} m_i$  is the total mass of the system,  $g$  is the gravitational acceleration constant, and  $r_y(t) = \frac{1}{m} \sum_{i=1}^{15} m_i r_{y,i}(t)$  is the position of the whole body center of mass in  $y$  direction, respectively.

## B. Human Experimental Results

1) *Gross assessment of balance ability:* As expected, Subject 1, who had no prior balance training, had worse balance performance than Subject 2, who was a trained gymnast. As summarized in Table II, Subject 1 was only able to maintain balance for approximately 23 seconds, whereas Subject 2 was able to maintain balance for just over 7 minutes. Subject 1 also had greater CoM motion compared to Subject 2.

2) *Patterns in angular momenta across body segments:* Fig. 2 depicts the time profiles of angular momenta from a representative portion (10 seconds) of each subject's trial. Note that the magnitude of angular momenta generated by the individual segments depended on the height and weight of subject. Despite clear differences in body stature and balance ability as indicated by trial time, the pattern of angular momenta generated by body segments was consistent across both subjects, which ran counter to our prediction. As illustrated in Fig. 2, the angular momenta of the individual upper body segments consistently acted opposite to the lower body segments.

Calculation of the cross correlation function between the total angular momentum of upper body segments,  $L_{ub}$ , and the lower body segments,  $L_{lb}$  confirmed this visual observation. The most negative cross correlation coefficient (Xcorr) was -0.95 for Subject 1 and -0.91 for Subject 2, indicating that the two signals were highly anti-correlated.

While  $L_{ub}$  and  $L_{lb}$  were highly anti-correlated, they did not cancel each other out. For both subjects, magnitude of  $L_{ub}$  was generally greater than the magnitude of  $L_{lb}$  over the course of each trial as described in Table II. As a result, there was significant whole body angular momentum  $L_{wb}$  about the beam axis throughout the entirety of each trial. Note that this same behavior was observed during balance beam walking as well [12].

3) *Estimate of external torque at foot-beam interaction port:* The RMS of external torque seen at the foot-beam interaction port was 9.72N·m for Subject 1 and 4.23N·m for Subject 2.

## III. DESCRIPTION OF BALANCING CONTROLLERS USED IN ROBOTICS RESEARCH

Developing balance control algorithms for bipedal robots has been a major research interest of the robotics community, and many of them have been implemented on complex real robotic platforms with demonstrated success. In this section, we identified a subset of controllers that produced balance behavior similar to what we observed in humans, namely that the angular momenta generated by the upper and lower body segments were anti-correlated. Based on the distinct behavior of upper body and lower body segments in the human data, we used a double inverted pendulum model. As such, we confined our work to test balance controllers compatible with this simple model.

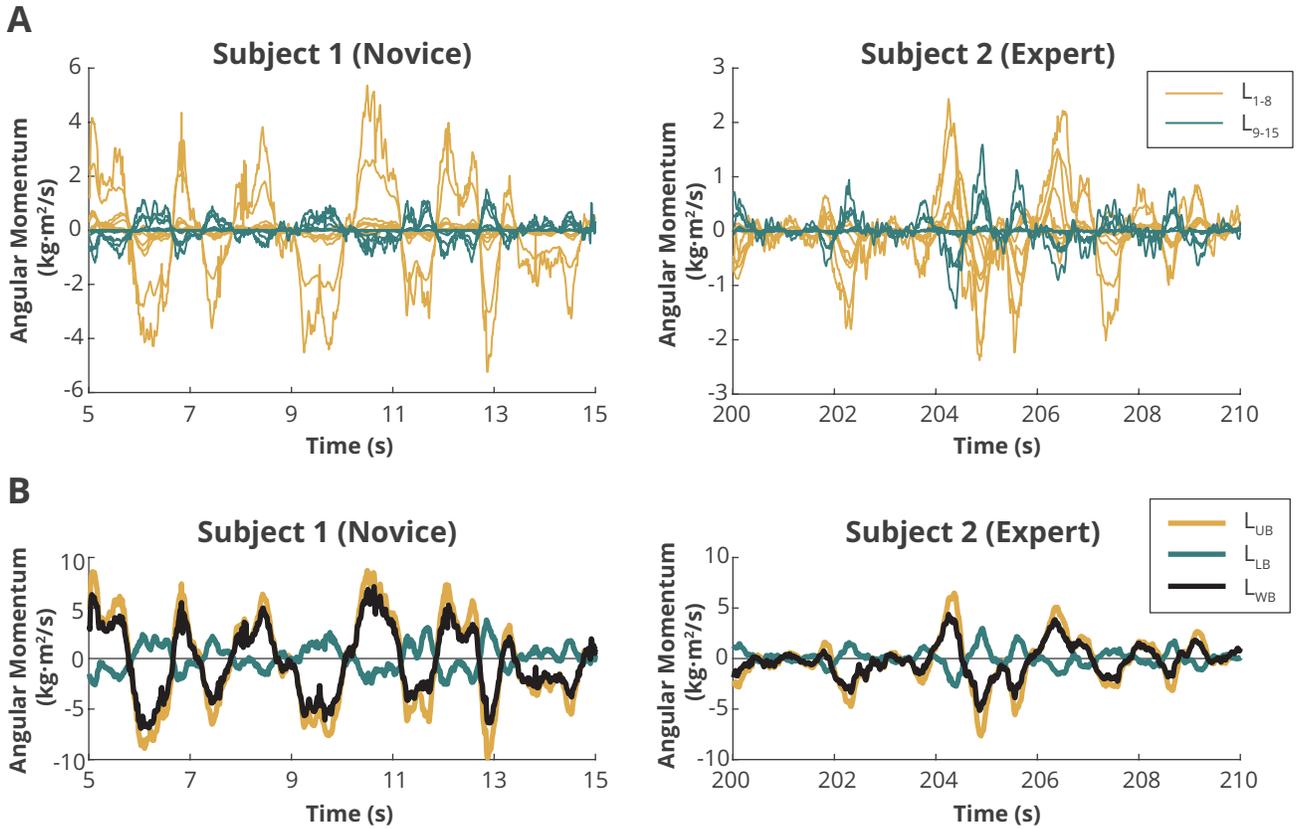


Fig. 2. Human experimental results. Profiles of angular momentum generated by (a) individual segments and (b) lumped upper body, lower body, and whole body segments. To visualize the observed patterns in angular momenta, data from only representative segment (10s) of each trial are shown.

TABLE III  
DOUBLE INVERTED PENDULUM MODEL PARAMETERS

Parameter	Meaning	Value [unit]
$m_1$	mass of link 1	28.36 [kg]
$l_1$	length of link 1	0.6960 [m]
$c_1$	center of mass of link 1	0.3480 [m]
$j_1$	moment of inertia of link 1 about its com	1.145 [kg·m <sup>2</sup> ]
$m_2$	mass of link 2	42.54 [kg]
$l_2$	length of link 2	1.044 [m]
$c_2$	center of mass of link 2	0.5220 [m]
$j_2$	moment of inertia of link 2 about its com	3.864 [kg·m <sup>2</sup> ]
$g$	gravitational acceleration	9.810 [m/s <sup>2</sup> ]

### A. Double Inverted Pendulum Model

The double inverted pendulum model we use for simulations is illustrated in Fig. 3. We can write the equations of motion as

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) = \boldsymbol{\tau}, \quad (6)$$

where  $\mathbf{M}(\mathbf{q}) \in \mathbb{R}^{2 \times 2}$  is the inertia matrix,  $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} \in \mathbb{R}^{2 \times 1}$  are the Coriolis and centrifugal terms,  $\mathbf{G}(\mathbf{q}) \in \mathbb{R}^{2 \times 1}$  are the gravitational torques, and  $\boldsymbol{\tau} = [\tau_1, \tau_2]^T \in \mathbb{R}^{2 \times 1}$  is the input torque vector. The relative coordinates  $\mathbf{q} = [q_1, q_2]^T \in \mathbb{R}^{2 \times 1}$  were chosen as a generalized coordinates to describe the model. The model parameters used for simulation are listed in Table III, which are obtained from [13], [14].

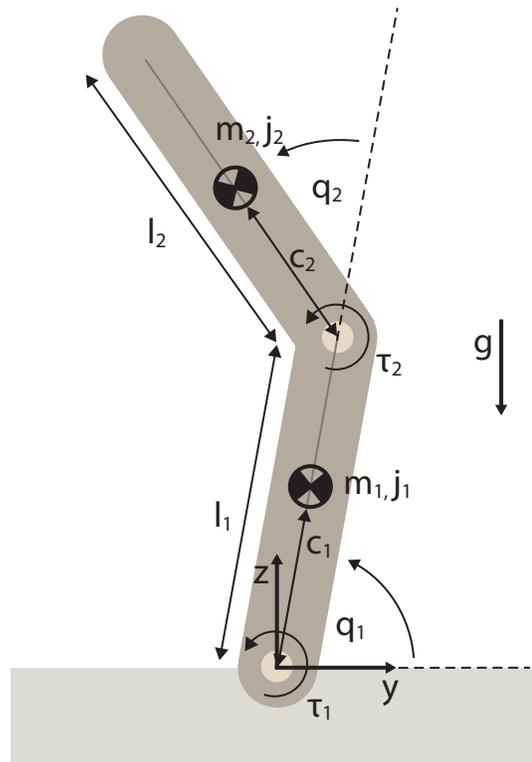


Fig. 3. Double Inverted Pendulum Model.

## B. Controllers

1) *Joint impedance controller (JIC)*: The simplest balancing controller is to implement virtual compliance either in joint (configuration) space or in the Cartesian (task) space. The joint impedance controller is defined as

$$\boldsymbol{\tau} = \mathbf{K}_{pj}(\mathbf{q}_0 - \mathbf{q}) - \mathbf{K}_{dj}\dot{\mathbf{q}}, \quad (7)$$

where  $\mathbf{K}_{pj}, \mathbf{K}_{dj} \in \mathbb{R}^{2 \times 2}$  are positive definite joint stiffness and damping matrices, respectively, and the rest position  $\mathbf{q}_0 = [\frac{\pi}{2}, 0]^T$  corresponds to the upright posture.

2) *Cartesian impedance controller (CIC)*: Alternatively, a virtual linear spring-damper supporting the center of mass of the model can also maintain balance,

$$\boldsymbol{\tau} = \mathbf{J}_{cm}^T (\mathbf{K}_{px}(\mathbf{r}_{cm,0} - \mathbf{r}_{cm}) - \mathbf{K}_{dx}\dot{\mathbf{r}}_{cm}), \quad (8)$$

where  $\mathbf{K}_{px}, \mathbf{K}_{dx} \in \mathbb{R}^{2 \times 2}$  are positive definite Cartesian stiffness and damping matrices, respectively, and  $\mathbf{r}_{cm}, \mathbf{r}_{cm,0}$  are the center of mass position and rest position of the virtual spring, respectively.

3) *Linear quadratic regulator (LQR)*: By defining the state variables as  $\mathbf{x} := [\mathbf{q}^T, \dot{\mathbf{q}}^T]^T$ , one can linearize the nonlinear equations of motion (6) about its equilibrium point,  $\mathbf{x}_*$  and  $\boldsymbol{\tau}_*$ , corresponding to the resting upright posture,

$$\dot{\bar{\mathbf{x}}} = \mathbf{A}_{lin}\bar{\mathbf{x}} + \mathbf{B}_{lin}\bar{\boldsymbol{\tau}}, \quad (9)$$

where  $\bar{\mathbf{x}} = \mathbf{x} - \mathbf{x}_*$  and  $\bar{\boldsymbol{\tau}} = \boldsymbol{\tau} - \boldsymbol{\tau}_*$  and  $\mathbf{A}_{lin}$  and  $\mathbf{B}_{lin}$  are linearized state and input matrices, respectively. The full-state linear quadratic regulator (LQR) takes advantage of the dynamic model of the system, and the choice of costs on deviation of states and actuation affects the controller gain  $\mathbf{K}_{LQR}$ .

$$\bar{\boldsymbol{\tau}} = -\mathbf{K}_{LQR}\bar{\mathbf{x}}. \quad (10)$$

4) *Natural posture recovery (NPR)*: The natural posture recovery (NPR) method presented by Abdallah and Goswami [15] is another simple, yet powerful, nonlinear controller for balance. Noting that upright posture corresponds to maximum potential energy that the system can have, one can design a control law to maximize the potential energy as below, with a positive gain  $k$ .

$$\dot{\mathbf{q}}^{\text{ref}} = k\mathbf{G}(\mathbf{q}) \quad (11)$$

$$\boldsymbol{\tau} = \mathbf{K}_{dj}(\dot{\mathbf{q}}^{\text{ref}} - \dot{\mathbf{q}}) \quad (12)$$

Here, the property that  $\mathbf{G}(\mathbf{q}) = \frac{\partial V(\mathbf{q})}{\partial \mathbf{q}}^T$  is used, where  $V(\mathbf{q})$  is the potential energy of the system. This control law leads the potential energy of the system towards global maximum, with some inevitable oscillation.

5) *Angular momentum based controller (AMBC)*: The last controller tested in this paper is the angular momentum based balance controller (AMBC) recently presented by Featherstone [16]. The controller assumes that only the hip is actuated to balance ( $\tau_1 = 0$ ). Let us denote the angular momentum of the total system about the supporting point

as  $L_{wb}$ . As the ankle torque is zero, the following relation holds.

$$L_{wb} = \mathbf{S}\mathbf{M}\dot{\mathbf{q}} \quad (13)$$

$$\dot{L}_{wb} = -mgr_y = -\mathbf{S}\mathbf{G} \quad (14)$$

$$\ddot{L}_{wb} = -mgr_y = -\mathbf{S}\frac{\partial \mathbf{G}}{\partial \mathbf{q}}\dot{\mathbf{q}} \quad (15)$$

where  $\mathbf{S} = [1 \ 0]$  is the selection matrix and  $r_y$  is the horizontal component of center of mass position. Consider the following control law.

$$\ddot{L}_{wb} = k_{dd}\ddot{L}_{wb} + k_d\dot{L}_{wb} + k_L L_{wb} + k_q(q_2 - q_2^d). \quad (16)$$

By taking the time derivative of (15), one can get  $\ddot{L}_{wb} = -mgr_y$  and the control torque  $\tau_2$  is computed by solving the inverse dynamics. The controller gains ( $k_{dd}, k_d, k_L$ , and  $k_q$ ) are chosen following the rule described in [16] which guarantees stability.

## IV. COMPARISON OF HUMAN BALANCE BEHAVIOR TO ROBOT CONTROLLER

### A. Simulation Details

Each controller was implemented on the same double inverted pendulum model with the same initial conditions. Furthermore, random ankle torque noise  $\tau_{1,\text{pert}}$  was added to simulate the variability observed in the human balancing experiment. The perturbation torque was assumed to follow a uniform distribution on the interval  $\tau_{1,\text{pert}} \in [-10, 10]$ N·m. This interval was chosen based on the RMS value of estimated torque seen at the point of foot-beam contact from Subject 1 (novice). The simulations were conducted using MATLAB (Mathworks, Inc., MA) `ode45` with default options.

The gains of each controller were empirically, but carefully, chosen such that the resultant center of pressure (CoP) deviation remained within  $\pm 2$ cm. This width was chosen to be close to the width of the beam (3.4cm).

### B. Simulation Results

The simulation results are shown in Fig. 4. For the six controllers tested, the time course of angular momentum about the support of whole body ( $L_{wb}$ ), upper body ( $L_{ub}$ ), and lower body ( $L_{lb}$ ) is plotted and the most negative/positive cross correlation coefficient between  $L_{ub}$  and  $L_{lb}$  is noted. In the LQR controller, ankle and hip actuation were equally penalized, whereas in the LQR<sub>hip</sub> controller, ankle actuation was largely penalized to suppress use of the ankle. Three controllers showed positive cross correlation (JIC: 0.88, LQR: 0.61, and NPR: 0.92). The other three controllers showed high anti-correlation with cross correlation coefficient less than -0.90 (CIC: -0.90, LQR<sub>hip</sub>: -0.94, and AMBC: -0.95).

Table IV summarizes the dependent measures of interest. The controllers that showed high anti-correlation of upper and lower body angular momentum are in bold font.

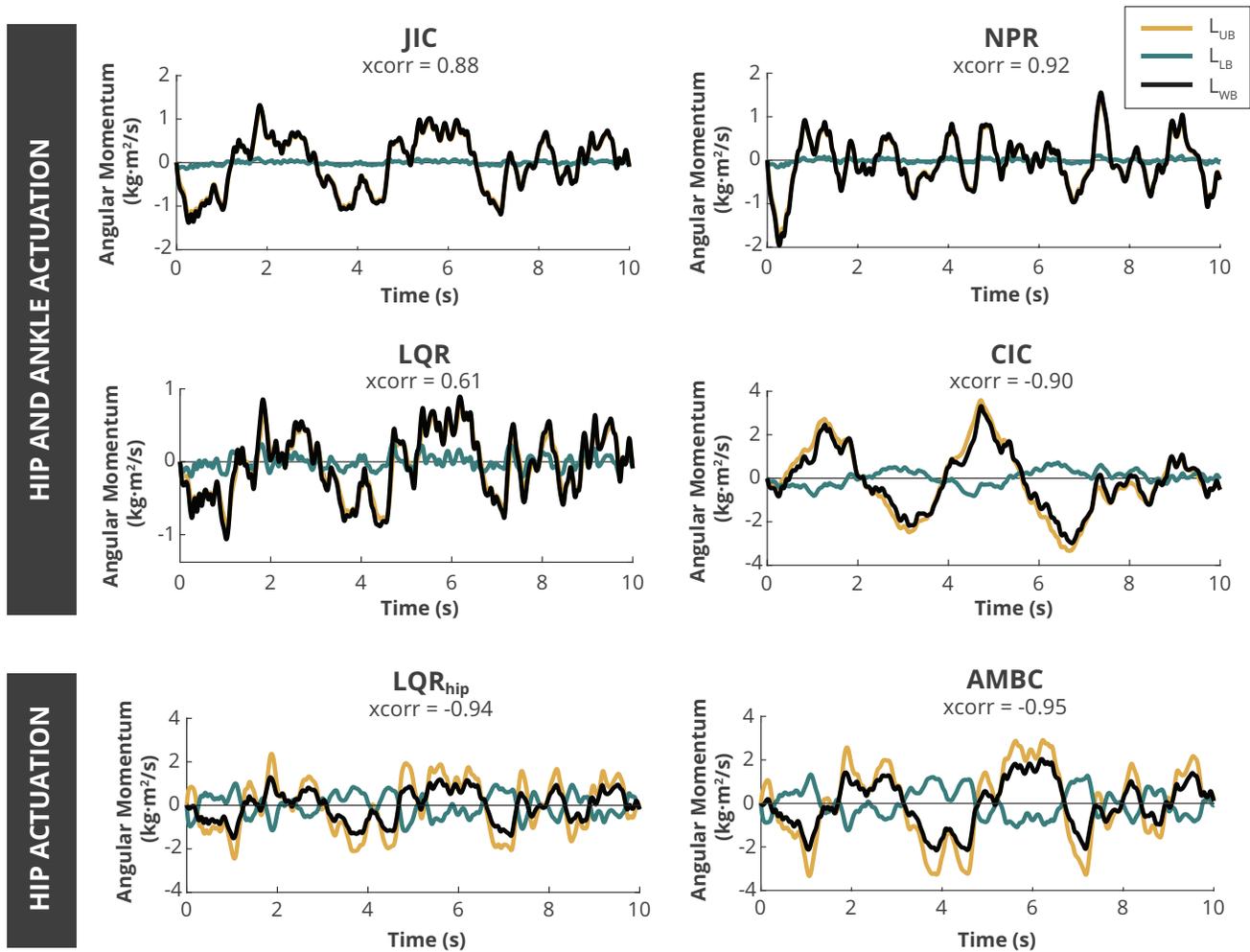


Fig. 4. Simulation results. Time course of angular momentum about the support of whole body (black), upper body (yellow), and lower body (green) for different six different balance controllers. The cross correlation coefficient between  $L_{ub}$  and  $L_{lb}$  of each system are denoted as well.

TABLE IV  
SUMMARY OF SIMULATION RESULTS

	CIC	LQR <sub>hip</sub>	AMBC	JIC	LQR	NPR
Xcorr	<b>-0.90</b>	<b>-0.94</b>	<b>-0.95</b>	0.88	0.61	0.92
RMS of $\tau_1$ , [N·m]	<b>6.49</b>	<b>0.967</b>	<b>0</b>	4.94	4.11	4.50
RMS of $\tau_2$ [N·m]	<b>32.0</b>	<b>17.1</b>	<b>28.3</b>	2.39	1.41	2.20
RMS of CoP [cm]	<b>1.0</b>	<b>0.70</b>	<b>0.72</b>	0.80	0.75	0.80

## V. DISCUSSION

For robotic devices designed to assist humans with balance, it is necessary that the assistance they provide does not interfere with the humans' intended behavior. Along the same vein, robotic devices used for rehabilitating or retraining balance ability need to guide users towards a desirable balance strategy. Hence, we sought to further characterize the intended and desired human behavior during balance such that future devices can be controlled to provide effective assistance.

The behavior observed from humans standing on the beam

revealed several important characteristics of mediolateral balance. First, while we did not constrain the subjects' arms, they generated angular momentum correlated with the thorax/abdomen such that the behavior of the upper body could be lumped into one segment. Second, the lumped upper body and lower body angular momenta were highly anti-correlated, meaning they acted in the opposite directions. The contribution of the upper body was significantly higher such that the overall whole-body angular momentum was non-zero.

Among the balance controllers we tested, three could reproduce the behavior we observed in the human experiment. Simulations with the LQR<sub>hip</sub>, AMBC, and CIC generated behavior with high anti-correlation between  $L_{ub}$  and  $L_{lb}$ . In these controllers, there was either no or little contribution of the ankle compared to the hip (Table IV). The remaining controllers we tested could not reproduce the high anti-correlation between  $L_{ub}$  and  $L_{lb}$ . Instead, the correlation was positive, meaning the double inverted pendulum became stiff and behaved like a single inverted pendulum. In these controllers, the contribution of ankle actuation was comparable

to or larger than hip actuation. Note that the CoP of the model with all controllers remained in a reasonable range as shown in Table IV. This may indicate that the observed human behavior was not as trivial as one might think; a narrow base of support (or support polygon) of the beam constrains the range of lateral CoP motion, but it *does not* necessarily limit the ability to actively use ankle. In this regard, while AMBC reproduced the observed anti-correlation of upper- and lower-body angular momentum, it imposed zero RMS ankle torque as shown in Table IV, which was not observed in human behavior.

Consistent across the different controllers tested here, correlation between  $L_{ub}$  and  $L_{lb}$  became less negative as the contribution of the ankle relative to the hip increased. Counter to our original prediction, comparison of human and simulation results suggest the behavior of the novice and the expert subjects could be described using the same controller: *a hip-dominant balancing*, but with slightly different levels of ankle actuation. Interestingly, the expert human subject had a lower anti-correlation between upper and lower body angular momentum than the novice subject. This suggests that the expert has slightly increased ankle contribution. Indeed, the difference between novice and expert in gross balance behavior could be reproduced in simulation by simply changing the gains of the LQR or CIC controllers. However, further human experiments are needed to test this speculation.

We emphasize that the purpose of this study was not to suggest how the human neuromuscular system controls balance, but rather to identify what type of simple models could competently describe the human behavior we observed. This is a subtle, yet important distinction. The human system is vastly complex. For instance, there are both passive and active compliance at the joints, significant time delays within the neuromotor system, and noise both in sensing and actuation. Even though none of these were considered in the models tested here, we were nevertheless able to identify controllers that adequately captured the anti-correlation of upper- and lower-body behavior. Moreover, at least three different hip-dominant balance controllers could replicate the observed human behavior. Further work is still needed to discern which is the most compatible with additional aspects of human balance behavior and neuromotor control. In general, it is also important to consider that the simplicity of observed motor behavior does not necessarily mean that the neuromuscular controller is simple as well.

In future work, we aim to extend this analysis and better understand how humans maintain mediolateral balance while walking on a beam, using simple and complex models of human locomotion. We also plan to examine how subtle changes in ankle contribution influence balance performance.

#### ACKNOWLEDGMENT

We graciously thank Dr. Enrico Chiovetto and Prof. Martin A. Giese for leading the design and execution of the human experiment.

#### REFERENCES

- [1] M. A. Schragger, V. E. Kelly, R. Price, L. Ferrucci, and A. Shumway-Cook, "The effects of age on medio-lateral stability during normal and narrow base walking," *Gait & Posture*, vol. 28, no. 3, pp. 466–471, 2008.
- [2] S. F. Tyson, M. Hanley, J. Chillala, A. Selley, and R. C. Tallis, "Balance disability after stroke," *Physical Therapy*, vol. 86, no. 1, pp. 30–38, 2006.
- [3] A. J. Young and D. P. Ferris, "State of the art and future directions for lower limb robotic exoskeletons," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 2, pp. 171–182, 2017.
- [4] H. I. Krebs and N. Hogan, "Robotic therapy: the tipping point," *American Journal of Physical Medicine & Rehabilitation*, vol. 9, no. 11, pp. S290–S297, 2012.
- [5] M. F. Levin, P. L. Weiss, and E. A. Keshner, "Emergence of virtual reality as a tool for upper limb rehabilitation: incorporation of motor control and motor learning principles," *Physical Therapy*, vol. 95, no. 3, pp. 415–425, 2015.
- [6] A. Domingo and D. P. Ferris, "Effects of physical guidance on short-term learning of walking on a narrow beam," *Gait & Posture*, vol. 30, no. 4, pp. 464–468, 2010.
- [7] —, "The effects of error augmentation on learning to walk on a narrow balance beam," *Experimental Brain Research*, vol. 206, no. 4, pp. 359–370, 2010.
- [8] J. L. Patton and F. A. Mussa-Ivaldi, "Robot-assisted adaptive training: custom force fields for teaching movement patterns," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 4, pp. 636–646, 2004.
- [9] D. J. Reinkensmeyer and J. L. Patton, "Can robots help the learning of skilled actions?" *Exercise and Sport Sciences Reviews*, vol. 37, no. 1, pp. 43–51, 2009.
- [10] S. M. O'Connor and A. D. Kuo, "Direction-dependent control of balance during walking and standing," *Journal of Neurophysiology*, vol. 102, no. 3, pp. 1411–1419, 2009.
- [11] A. Sawers, J. L. Allen, and L. H. Ting, "Long-term training modifies the modular structure and organization of walking balance control," *Journal of Neurophysiology*, vol. 114, no. 6, pp. 3359–3373, 2015.
- [12] E. Chiovetto, M. E. Huber, D. Sternad, and M. Giese, "Low-dimensional organization of angular momentum during walking on a narrow beam," *Scientific Reports*, vol. 8, no. 1, p. 95, 2018.
- [13] I. D. Loram and M. Lakie, "Direct measurement of human ankle stiffness during quiet standing: the intrinsic mechanical stiffness is insufficient for stability," *The journal of physiology*, vol. 545, no. 3, pp. 1041–1053, 2002.
- [14] T. Insperger, J. Milton, and G. Stépán, "Acceleration feedback improves balancing against reflex delay," *Journal of the Royal Society Interface*, vol. 10, no. 79, p. 20120763, 2013.
- [15] M. Abdallah and A. Goswami, "A biomechanically motivated two-phase strategy for biped upright balance control," in *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*. IEEE, 2005, pp. 1996–2001.
- [16] R. Featherstone, "A simple model of balancing in the plane and a simple preview balance controller," *The International Journal of Robotics Research*, vol. 36, no. 13-14, pp. 1489–1507, 2017.