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Center of mass kinematics robustly predict multidirectional reactive joint torques during perturbed standing

Kristen L. Jakubowski[1], *Member, IEEE*, Gregory S. Sawicki[2-5], *Member, IEEE*, and Lena H. Ting[1,6], *Member, IEEE*

***Abstract*—Recently, exoskeleton controllers have been developed to augment balance. However, controllers have not been validated against multidirectional perturbations, and only actuate a single joint without considering the coordinated multi-joint response required to maintain balance. By leveraging the human physiological response to postural perturbations, we may be able to overcome these limitations. We have developed a sensorimotor response model (SRM) for perturbed standing balance that robustly predicts the coordinated activations of lower limb muscles based on center of mass (CoM) kinematics. Recently, a modified version of the SRM was used to reconstruct sagittal plane ankle torque during perturbed standing and walking. Building on this work, we further modified the SRM so it could predict the multi-joint torque response. Using the newly modified CoM-driven SRM, we reconstructed joint torques at the ankle, knee, and hip in response to support surface perturbations in 8 different directions during standing (0, 45, 90, 135, 180, 225, 270, 315°) with good temporal accuracy. Notably, the SRM was only tuned in the 4 cardinal directions (0, 90, 180, 270°), after which it could predict the torque response in the diagonal directions (45, 135, 225, 315°). With the average R^2 and VAFs across all joints and perturbation directions of 0.83 and 0.84, respectively, our results support the viability of the SRM as an exoskeleton controller to augment balance in response to perturbations in varying directions. A controller that uses a single control vector, CoM kinematics (e.g., one-to-many), rather than one that needs a control signal for every joint (e.g., one-to-one) may simplify the control of exoskeletons, as well as bipedal robots, and lower-limb prostheses.**

I. Introduction

Lower limb exoskeletons are tools for enhancing mobility in older adults and individuals with neuromuscular injuries or pathologies [1-3]. However, despite serious demand from stakeholders who consider fall prevention the most important design goal not yet addressed [4], nearly all current exoskeletons aim to improve the economy of steady-state walking [5-7]. Only recently have exoskeletons begun to be used to augment balance [8-11]. Given this nascent objective in the field, there remain several open questions. First, current controllers have not been evaluated against perturbations with varying spatial features. Perturbations that differ in magnitude and direction challenge balance in very different ways [12, 13]. Thus, the ideal exoskeleton control scheme should be robust to perturbations with varying spatial features. Second, successful reactive balance control requires coordinated modulation of hip and ankle torques, with the engagement of each joint varying depending upon the spatial features of the perturbation [14, 15]. Yet, current balance-augmenting exoskeletons actuate either the ankle [8, 9] or hip [10, 11] without considering the coordinated multi-joint response. For the potential of exoskeletons to enhance balance to be realized, the device and controller must be robust to a diverse range of perturbations and the human physiological response.

A sensorimotor response model (SRM) of the human physiological response to postural perturbations has the potential to overcome previous limitations and augment balance in response to varying perturbations. An error-based sensorimotor transformation of the delayed center of mass (CoM) kinematics (e.g., acceleration, velocity, and displacement) robustly explains the reactive muscle activations occurring in response to perturbations of varying directions and amplitudes [16-19]. The SRM is based on the principle that the neuromuscular system coordinates the activation of muscles across the body to maintain task-level goals, such that coordinated muscle activations reflect task-relevant errors (e.g., CoM displacement) as opposed to joint-level errors or sensory inflow [19]. By leveraging this physiological principle, we may be able to predict the coordinated multi-joint torque response. Afschrift, et al. [20] recently modified our previously developed SRM to estimate the balance-correcting torque about the ankle during standing and walking, and has since implemented this model on an ankle exoskeleton to augment balance in response to waist push and pull perturbations in the sagittal plane [8]. Building on this work, our preliminary results demonstrate CoM kinematics not only predict the response at the ankle, but also at the knee and hip during standing support-surface perturbations of varying magnitudes (up to 95% of step threshold, ~21cm) in the sagittal plane [21, 22]. However, it remains an open question if the SRM can predict the torque response to perturbations in varying directions.

Here, we evaluated the accuracy of a CoM-driven SRM at predicting the torque response to support-surface perturbations in varying directions during standing balance at 1) multiple joints (e.g., ankle, knee, and hip) and 2) in multiple planes (e.g., hip flexion/extension and hip ab/adduction). We expect that the SRM's ability to predict muscle activations will

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1Wallace H. Coulter Department of Biomedical Engineering, Emory University and Georgia Institute of Technology, Atlanta, GA, 30322, USA. 2George W. Woodruff School of Mechanical Engineering, 3Insitute for Robotics and Intelligent Machines, 4School of Biological Sciences, Georgia Institute of Technology, Atlanta, GA, 30322, USA. 5Institute for Human Machine Cognition, Pensacola, FL, 32502, USA. 6Department of Rehabilitation Medicine, Division of Physical Therapy, Emory University, Atlanta, GA, USA. kjakubo@emory.edu, gregory.sawicki@me.gatech.edu, lting@emory.edu. Corresponding author: K. L. Jakubowski.

transfer to accurate predictions of the torque at each joint—performance that would support the future implementation of this approach within an exoskeleton to augment balance.

II. Methods

A. Participants

Four healthy young adults (22 ± 4 years; 1 male) participated in this ongoing experiment. All participants were free of neuromuscular injuries and gave informed consent to the experimental protocol, which was approved by the Emory University Institutional Review Board.

B. Data collection

Participants were instructed to maintain their balance in response to ramp and hold support surface translations. Participants stood with their bare feet approximately 22cm apart on independent force plates and arms crossed about their torso. A 33-marker set based on a modified version of the Vicon Plug-in Gait model [16] that included additional foot markers (fifth metatarsal, medial and lateral heel, and medial malleolus) was used. All kinetic data (1000 Hz) were synchronized with kinematic data (collected at 100 Hz) using a motion capture system (Vicon, UK, Oxford).

To quantify the reactive joint torques to perturbations in different directions, participants completed 40 ramp-and-hold support surface perturbations in 8 different directions: 0, 45, 90, 135, 180, 225, 270, and 315°. All perturbations had a displacement of 12.6 cm, a velocity of 24 cm/s, and an acceleration of 1.6 G (Fig 1). This work is part of a larger ongoing study with multiple perturbation magnitudes, where the perturbations are scaled to occur over the same time span.

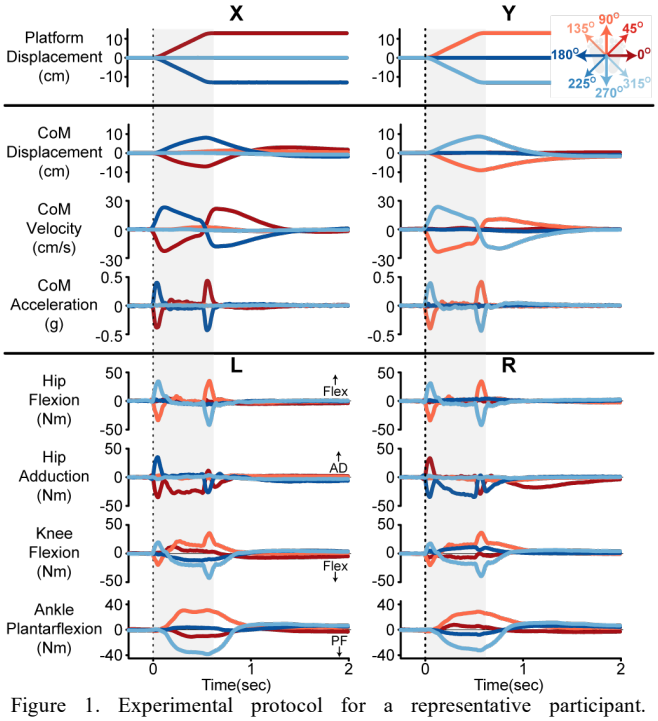

Figure 1. Experimental protocol for a representative participant. Participants were instructed to maintain a foot-in-place response to 12.6 cm perturbations in 8 directions. All torques represent the change from the baseline, pre-perturbation value. The dashed line indicates the start of the perturbation, while the shaded region indicates the perturbation duration. For ease of viewing only the traces in the cardinal directions are shown. CoM = center of mass, PF = plantarflexion, Flex = flexion, AD = adduction.

Each perturbation was delivered 5 times in a randomized fashion.

C. Data Processing

Ground reaction forces and limb segment marker data were used to estimate joint kinematics and kinetics. Ground reaction forces were filtered using a fourth-order low-pass filter with a 50 Hz cutoff, while marker data was filtered with a 10 Hz cutoff. Ankle, knee, and hip kinetics were estimated using the inverse dynamics (ID) toolbox in OpenSim using the OpenSim Gait 2892 model [23]. We calculated horizontal CoM acceleration as the summed horizontal ground reaction forces from each leg divided by the participant's mass and the platform acceleration, while CoM displacement and velocity were calculated as the sum of segmental kinematics weighted by corresponding segmental masses. All CoM kinematics are relative to the base of support. CoM displacement and velocity were up-sampled to 1000 Hz for all further analysis. Perturbation trials that elicited a stepping response or participants uncrossed their arms were excluded from further analyses as joint torques cannot be estimated when they step off the force plate. Stepping responses were identified as trials in which the magnitude of ground reaction forces for either leg dropped below 10 N.

D. Sensorimotor response model (SRM)

We evaluated whether the SRM predicted multi-joint torque responses to perturbations in varying directions for both the right and left leg. The previously developed SRM reconstructs reactive muscle activations as a linear combination of CoM kinematics at a common delay (Eq 1).

$$EMG_i = k_d\boldsymbol{d}(t-\lambda) + k_v\boldsymbol{v}(t-\lambda) + k_a\boldsymbol{a}(t-\lambda) \quad (1)$$

where k_d, k_v, and k_a are the feedback gains on CoM displacement (d), velocity (v), and acceleration (a), and λ is the time delay. We made two main modifications to this model to reconstruct the joint torques (Fig 2). The prior model looked at muscle-level responses, and muscles can only produce forces, and thus torques, in one direction (e.g., muscles only pull). In contrast, joint-level responses are the net effect of the activation of all muscles about that joint. Thus, to capture the bi-directional nature of the torque response, parallel loops of differing signs were added to capture the contributions of agonist and antagonist muscles (e.g., positive and negative torque response; Fig 2), and to predict the torque response to both CoM acceleration and deceleration (e.g., the positive and negative components of the input; Fig 2). Thus, ultimately, for all joints, the SRM model consisted of 4 loops, with two loops corresponding to the positive torque response – one loop corresponding to the positive components of the input and one loop corresponding to the negative components of the input. The same structure was used to predict the negative torque response (Fig 2).

The gains and delays within each loop were tuned to optimize the fit between the ID-derived and the SRM-derived joint torques for each participant, perturbation direction, and joint. First, the trials in the same perturbation direction were averaged. Next, the background torque was identified as the average torque 1 second before the onset of the perturbation, and this was removed from the overall torque response prior to SRM fitting. For the two loops reconstructing the positive torque response, hand-tuned optimization was performed to

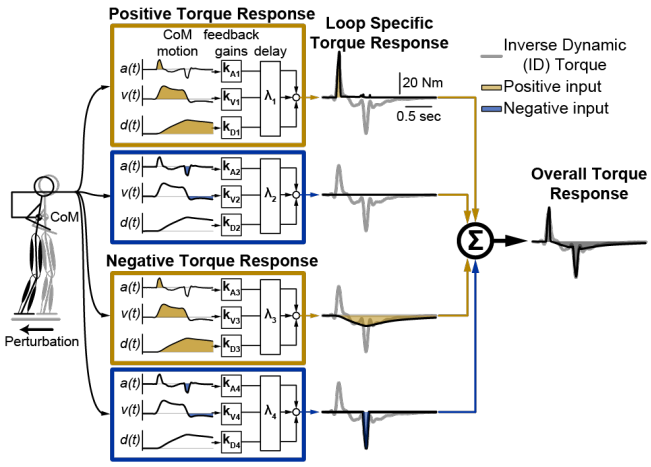

Figure 2. Joint torque was estimated as the quasi-linear sum of CoM deviation. Parallel loops, each with independent gains and delays, are used to estimate the positive and negative components of the output (joint torque) and corresponding to the positive and negative components of the input (CoM deviation). Note: This is the model for hip flexion torque in response to the perturbation at 270°, where there was no positive torque response corresponding to the deceleration (e.g., negative input) of the CoM. Thus, those gains are zero.

identify k_{di}, k_{vi}, $k_{ai,}$ and λ_i (where i indicates the ith SRM loop). This involved an initial optimization and then adjusting the bounds on the gains to prevent the loops from reconstructing the same components of the response. After optimizing the gains corresponding to the positive and negative components of the input, the gains and delays were concatenated into an initial guess for a final optimization, which concurrently optimized the gains for both loops. The same procedure was performed to reconstruct the negative torque response. If there was no corresponding torque response (as illustrated by the lack of a positive hip torque response for the second loop, Fig 2) or the additional loop did not improve the quality of the fit (e.g., increase the R^2 and VAF), the gains and delay for that loop were set to zero.

We tested the ability of the SRM to reconstruct the torque response in the cardinal directions and to generalize from the cardinal directions to the diagonals. Thus, the gains and delays for all joints were estimated for the 4 cardinal directions (e.g., 0, 90, 180, and 270°; "trained"; Fig 1–thick arrows), and these gains were used to predict the torque response in all other directions ("validated"; Fig 1–thin arrows). When determining the gains for the forward/backward perturbations (90 and 270°), CoM deviation in the sagittal plane (Fig 1: CoM Y) was the input into the SRM, while CoM deviation in the frontal plane (Fig 1: CoM X) was the input to the right/left perturbations (0 and 180°). When using the gains to predict the torque response to perturbations in the other directions (45, 135, 225, and 315°), the X and Y gains were from perturbations within the same quadrant. For example, for the perturbation at 45°, the X gains were from the 0° perturbation, while the Y gains were from the 90° perturbation. In contrast, for the perturbation at 225°, the X gains were from the 180° perturbation, and the Y gains were from the 270° perturbation. This was done to account for the asymmetric response between the right and left leg during right/left perturbations (e.g., one leg abducting while the other adducts; Fig 1).

We evaluated the quality of the SRM reconstruction by quantifying the R^2 (squared center Pearson's correlation coefficient) and VAF (the square of Pearson's uncentered correlation coefficient) between the ID-derived and the SRM-derived joint torques. We also estimated the root mean square error (RMSE) between the ID-derived and the SRM-derived joint torques. The RMSE was normalized by the range of the ID torque. All metrics are reported as the mean ± standard deviation unless otherwise noted. For brevity, the data presented are for the left leg. Results were similar for torques in the right leg.

III. Results

Qualitatively, the SRM reconstructed the time history of the joint torque response at the hip, knee, and ankle in the trained directions (e.g., the cardinal directions), as well as in the validated directions (e.g., the diagonals; Fig 3). For example, for the hip flexion response at both 270 and 225°, the SRM captured the peaks occurring at the onset and end of the perturbation (start and end of the shaded region – Fig 3); the same was observed for hip adduction and knee flexion. In all three joints, the SRM predicted the torque response during the perturbation (shaded region) with good temporal accuracy. Lastly, the CoM-driven SRM was able to capture all salient features of the torque response at all joints (ankle, knee, and hip), that continued after the perturbation ended (non-shaded region – Fig 3). These results indicate that if implemented as a torque control algorithm on exoskeleton hardware, the assistive torque profile would be temporally similar to the biological torque.

Quantitatively, across all directions, and all joints, the SRM predicted the biological joint torque response with the mean R^2 and VAFs across all joints and perturbation directions of 0.83 and 0.84, respectively. Across all joints, the SRM fit the torque response better in the trained directions, but also performed well in the validated directions (Tables I & II, Fig 4).

While the base structure of the SRM had 16 independent parameters, fitting the response at each joint required far fewer parameters. The model needed extra parameters so a single model could predict the response in all directions. For

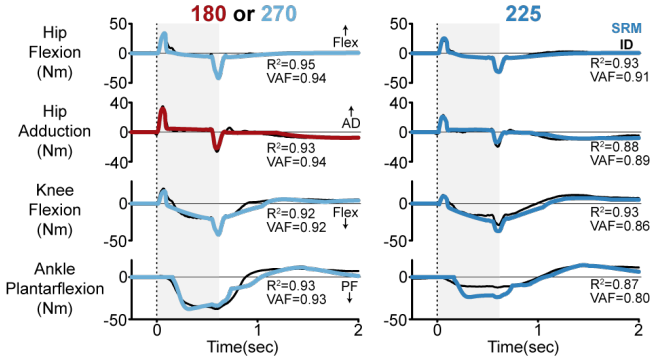

Figure 3. Representative fits for the CoM-driven SRM for perturbations in a trained direction (180 – red for hip adduction and 270 – light blue for ankle plantarflexion, knee flexion, and hip flexion). These directions are presented since they are the directions where the torque was the largest. Representative fit in a validated direction (e.g., 225 – darker blue). The dashed line indicates the start of the perturbation, while the shaded region indicates the perturbation duration. PF = plantarflexion, Flex = flexion, AD = adduction. Data presented are for the left leg. The black line is the inverse dynamic-derived joint torques.

example, at the ankle, for all participants, there was no negative torque response corresponding to the negative components of the CoM kinematics when fitting the response to sagittal plane perturbations at 90 and 270° (bottom loop in Fig 2), but there was when fitting the response to frontal plane perturbations at 0 and 180°. On average, 6 ± 1 parameters were needed to predict the ankle plantarflexion response, and 8 ± 2 for the knee flexion, hip flexion, and hip adduction response.

TABLE I. MEAN FITS TRAINED DIRECTIONS

	Hip Flexion	*Hip Adduction*	*Knee Flexion*	*Ankle Plantarflexion*
R^2	0.87 ± 0.08	0.79 ± 0.17	0.92 ± 0.05	0.92 ± 0.05
VAF	0.88 ± 0.11	0.81 ± 0.19	0.93 ± 0.05	0.93 ± 0.06
RMSE (%)	5 ± 2	3 ± 2	3 ± 3	4 ± 2

TABLE II. MEAN FITS VALIDATED DIRECTIONS

	Hip Flexion	*Hip Adduction*	*Knee Flexion*	*Ankle Plantarflexion*
R^2	0.83 ± 0. 09	0.73 ± 0.13	0. 78 ± 0.20	0.80 ± 0.21
VAF	0.84 ± 0.08	0.74 ± 0.14	0.80 ± 0.23	0.82 ± 0.23
RMSE (%)	5 ± 2	5 ± 3	7 ± 2	11 ± 5

IV. DISCUSSION

Here, we show the capability of a CoM-driven sensorimotor response model (SRM) to estimate the multi-joint torque response to balance perturbations in varying directions during standing. The CoM-driven SRM met both design criteria of being able to predict the response 1) at multiple joints (e.g., the ankle, knee, and hip), and 2) in multiple planes (e.g., hip flexion/extension and hip ab/adduction). Moreover, SRM gains tuned to fit joint torques in the cardinal directions generalized to other directions, predicting torque responses to diagonal perturbations. In addition to our findings here, our prior preliminary work has demonstrated that the SRM can predict the multi-joint response to sagittal plane perturbations of varying magnitudes during standing, including perturbations larger than tested here [21, 22]. The SRM has also been used to explain the balance-correcting response at the ankle during walking [8, 20]. Collectively, these results suggest that we may be able to use a single control vector (CoM kinematics) to drive a multi-joint exoskeleton that restores, assists, or augments balance in response to a diverse range of perturbations and movement contexts. The ability to use a single control signal to robustly predict the torque response at multiple joints can simplify the control of lower-limb robotic exoskeletons aimed at augmenting balance.

The CoM-driven SRM is based on physiological principles underlying the global human balance-correcting response to postural perturbations, and enabled us to train the model on the cardinal directions and predict the responses in the diagonals. As such, the model only required training data from a few directions to predict the response in multiple directions. While we only tested every 45°, the SRM should also generalize to any of the off-axis angles. For example, the SRM has been shown to predict the coordinated muscle activation response to perturbations in 30° increments [12]. Additionally, when predicting muscle activations, we can tune feedback gains for one direction and generalize them to other directions using a cosine-tuning rule [19].

We could have employed other methods, including splines or machine learning, to predict the biological torque response, but these methods likely would not exhibit the same generalizability as we found in the SRM. Determining the desired exoskeleton torque profile by optimizing nodes on a spline has been quite effective in minimizing the metabolic cost of walking [6, 24]. However, to implement splines into a balance-augmenting exoskeleton, individual spline fits would be required for each possible perturbation direction—a daunting task when considering the sheer number of need to be specified. For example, the torque spline tuned to optimize the balance response at one joint for a perturbation of a given magnitude and direction (e.g., optimal exoskeleton ankle torque to arrest a mediolateral standing balance perturbation) would likely not generalize to other perturbation magnitudes or directions (e.g., optimal hip exoskeleton torque to arrest a fore-aft standing balance perturbation). This is evidenced by the peak hip flexion torque in the first 250 ms being larger during the 270° perturbation compared with the 225° perturbation (Fig 3), which would result in different spline parameters being needed to capture this difference. Another alternative to the CoM-driven SRM is to take a data-driven machine-learning approach. Recent advances in machine learning have demonstrated that I/O models (e.g., temporal convolutional networks; TCN) can be trained on a subset of

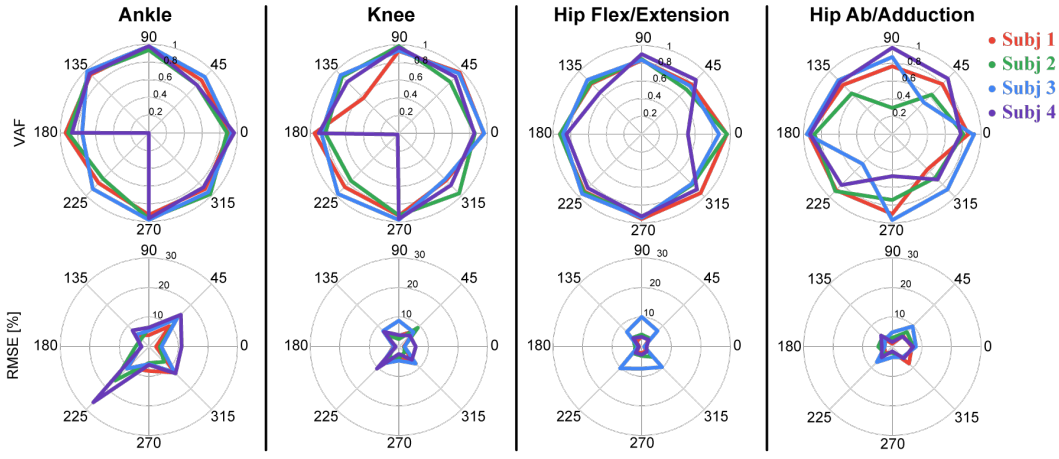

Figure 4. At almost all joints in all directions, the SRM reconstructed the inverse dynamics derived torques well (VAF > 0.7). While not illustrated, results are similar when examining R^2. The root mean squared error (RMSE) between the SRM reconstructed and ID torques was low (e.g., <10%) at most joints and directions. Note that the SRM was only optimized in the cardinal directions. Different colors represent different participants.

locomotion data and then used to predict the biological torque responses across a range of 'unseen' conditions [25, 26]. While machine learning is a promising approach, it remains unknown how similar the training and 'unseen' conditions need to be for generalization. Thus, it's unclear if a machine learning model could be trained on data from only the cardinal directions and generalize to the unseen directions, as we demonstrated here with the CoM-driven SRM.

The CoM-driven SRM resulted in precise temporal predictions based on task-level goals, while requiring little data to train and relatively few parameters to capture the complexity of the response. On average, the number of parameters needed to fit the SRM was similar to those used within splines for metabolic cost reduction [24]. Splines of the desired exoskeleton torque assistance with as few as 4 parameters to as many as 10 are used to optimize assistance for energetic efficiency, with more parameters needed to capture more complex shapes [6, 24]. While the number of parameters was similar, the SRM required significantly less data compared to other methods. Participants only needed to complete approximately 20 trials, with each trial lasting less than 5 seconds—for a total of less than 2 minutes of data collection—to find the SRM gains in the cardinal directions. The postprocessing tuning SRM parameters for each participant required less than 1 hour. Optimizing the spline parameters requires hours of data collection [6, 24]. Similarly, while machine learning is a promising approach for predicting the biological torque responses [25, 26], it requires significantly more data and time than what was needed to optimize the CoM-driven SRM. For example, to reach R^2 values similar to what we report here, typically TCNs need >1 million unique labels from data sets with large heterogeneity [25].

Using a control framework that mimics the biological response to postural perturbations may improve the learning and embodiment of the exoskeleton. Principles of embodiment suggest that robotic devices should coordinate with humans' natural responses such that the nervous system can model the controller of the robotic device [27]. Since a CoM-driven SRM control scheme is based on the nervous system's stereotypical response, it should provide a torque profile that is already familiar to the user. So, it may be easier for the individual to learn to use the device because it attempts to mimic their own physiological response. We also acknowledge, however, that the biological response to postural perturbations is a higher-order process, and the SRM leverages a reduced-order description of a complex system. If the physiologically-based control scheme is too complex or there are errors present within the controller, it may actually make it *more* difficult for a user to learn to use their device under SRM control. Identifying how the structure of different control schemes impacts the learning of and adaptation to devices is an underexplored area of research that will need to be expanded to determine the best control framework to facilitate learning and embodiment of balance-augmenting devices.

In addition to providing a framework for exoskeleton control, the CoM-driven SRM can unlock information about the underlying neuromuscular system. For example, we have previously demonstrated that, by examining the delays associated with each sensorimotor loop in the model structure, it is possible to dissociate the intrinsic and neurally mediated components of the torque response at each joint [21]. Thus, it has great potential to be used as a diagnostic tool to help identify sources of impairments in the neuromuscular response to postural perturbations due to aging, injury, or disease. Using the SRM to 'reverse-engineer' sources of sensorimotor impairment could aid in the development of personalized rehabilitation interventions for improving balance. Alternative modeling frameworks that can describe input-output responses of the human sensorimotor system (e.g., machine learning approaches), often lack explicit physiological insight into *what* subsystems are mediating the multi-joint torque response. Model-based or physics-based machine learning may be able to overcome this limitation and provide physiological information. However, for this to occur, we need to develop interpretable AI, where there is an underlying, physiologically-inspired structure embedded in the machine learning model.

A. Limitations and Future Work

One limitation of the current work is that we only tested a single magnitude of support surface perturbations, 12.6 cm. This was the largest perturbation we could perform with the perturbation direction randomized. This perturbation size poses only a small challenge to balance for healthy young adults, which may be handled primarily via an ankle strategy, especially for perturbations in the sagittal plane. While an ankle strategy is the primary strategy in the sagittal plane, it is not in the frontal plane, where all measured inversion/eversion torques were below ~5 Nm, and thus, we did not fit the SRM to these torques. The SRM should be tested on larger perturbation magnitudes in different directions to thoroughly examine the generalizability of this approach.

Another limitation is that the SRM did not fit the response well for subject 4 for the 225° perturbation at the ankle and knee (Fig 4). This could be indicative of that participant using a unique balance strategy for this perturbation direction. Further work is required to evaluate and improve the robustness of the SRM to predict the biological torque when individuals employ unique balance strategies.

An important next step will be to deploy our CoM-driven SRM-based framework as a control scheme on exoskeleton hardware and evaluate its efficacy in augmenting standing balance. There are a few key challenges and questions related to this implementation. First, as mentioned previously, the SRM can partition the rapid intrinsic mechanical response that occurs at the time of the perturbation from the delayed neurally-mediated feedback response from the total torque response at each joint. However, due to bandwidth limitations of robotic actuators and the delays associated with identifying that a perturbation occurred, it will not be possible to actuate at the instant of the perturbation onset (i.e., actively controlled actuators on a robotic device cannot mimic the instantaneous intrinsic mechanical response of muscles). What are the implications of not providing the intrinsic mechanical response, both in terms of augmenting the balance-correcting response but also on how individuals perceive the assistance? Second, based on prior work, an ankle exoskeleton can enhance balance when assistance is applied faster than the user's muscular response, but not when it's applied concurrently [28]. Within the multi-loop SRM, it is possible

to directly specify the delays associated with each loop and set shorter controller delays that provide a faster than the biological response. However, will it be best to actuate all control loops faster or just some (e.g., faster than the human ankle but not the hip?) Additionally, how much faster than the human response should we actuate, and is this the same for each loop? Lastly, recent evidence suggests that applying biological torques enhances balance [8]. However, when optimizing metabolic cost, the optimal exoskeleton controller may not be a scaled version of the biological torque [29]. Future work is still required to determine the optimal assistance profile for balance augmentation. As we move to implement the CoM-driven SRM control framework on exoskeleton hardware, answers to these questions will come into focus.

V. Conclusion

In this work, we demonstrate that a CoM-driven sensorimotor response model (SRM) can predict the reactive torque response at the hip, knee, and ankle to balance perturbations in varying directions. This is a promising proof-of-concept that a CoM-driven SRM-based exoskeleton control paradigm could robustly augment balance performance across an array of perturbations with varying spatial properties.

References

[1] L. N. Awad *et al.*, "A soft robotic exosuit improves walking in patients after stroke," *Science translational medicine,* vol. 9, no. 400, p. eaai9084, 2017, doi: 10.1126/scitranslmed.aai9084.

[2] A. Esquenazi, M. Talaty, A. Packel, and M. Saulino, "The ReWalk powered exoskeleton to restore ambulatory function to individuals with thoracic-level motor-complete spinal cord injury," *American journal of physical medicine & rehabilitation,* vol. 91, no. 11, pp. 911-921, 2012.

[3] Z. F. Lerner, D. L. Damiano, and T. C. Bulea, "A lower-extremity exoskeleton improves knee extension in children with crouch gait from cerebral palsy," *Science translational medicine,* vol. 9, no. 404, p. eaam9145, 2017.

[4] J. Wolff, C. Parker, J. Borisoff, W. B. Mortenson, and J. Mattie, "A survey of stakeholder perspectives on exoskeleton technology," *Journal of neuroengineering and rehabilitation,* vol. 11, no. 1, pp. 1-10, 2014.

[5] S. H. Collins, M. B. Wiggin, and G. S. Sawicki, "Reducing the energy cost of human walking using an unpowered exoskeleton," *Nature,* vol. 522, no. 7555, pp. 212-215, 2015.

[6] J. Zhang *et al.*, "Human-in-the-loop optimization of exoskeleton assistance during walking," *Science,* vol. 356, no. 6344, pp. 1280-1284, 2017.

[7] R. Nuckols, S. Lee, K. Swaminathan, D. Orzel, R. Howe, and C. Walsh, "Individualization of exosuit assistance based on measured muscle dynamics during versatile walking," *Science Robotics,* vol. 6, no. 60, p. eabj1362, 2021.

[8] M. Afschrift *et al.*, "Assisting walking balance using a bio-inspired exoskeleton controller," *Journal of neuroengineering and rehabilitation,* vol. 20, no. 82, 2023.

[9] C. Bayón, A. Q. Keemink, M. van Mierlo, W. Rampeltshammer, H. van der Kooij, and E. H. van Asseldonk, "Cooperative ankle-exoskeleton control can reduce effort to recover balance after unexpected disturbances during walking," *Journal of neuroengineering and rehabilitation,* vol. 19, no. 1, pp. 1-16, 2022.

[10] T. Zhang, M. Tran, and H. Huang, "Design and experimental verification of hip exoskeleton with balance capacities for walking assistance," *IEEE/ASME Transactions on mechatronics,* vol. 23, no. 1, pp. 274-285, 2018.

[11] V. Monaco *et al.*, "An ecologically-controlled exoskeleton can improve balance recovery after slippage," *Scientific reports,* vol. 7, no. 1, pp. 1-10, 2017.

[12] Safavynia SA and T. LH, "Task-level feedback can explain temporal recruitment of spatially fixed muscle synergies throughout postural perturbations," *Journal of neurophysiology,* vol. 107, no. 1, pp. 159-177, 2012.

[13] J. K. Leestma, P. R. Golyski, C. R. Smith, G. S. Sawicki, and A. J. Young, "Linking whole-body angular momentum and step placement during perturbed human walking," *Journal of Experimental Biology,* vol. 226, no. 6, p. jeb244760, 2023.

[14] F. B. Horak and J. M. Macpherson, "Postural orientation and equilibrium," *Handbook of Physiology,* vol. 1, pp. 255-292, 1996.

[15] M. Vlutters, E. H. van Asseldonk, and H. van der Kooij, "Lower extremity joint-level responses to pelvis perturbation during human walking," *Scientific Reports,* vol. 8, no. 1, pp. 1-12, 2018.

[16] T. D. Welch and L. H. Ting, "A feedback model reproduces muscle activity during human postural responses to support-surface translations," *Journal of neurophysiology,* vol. 99, no. 2, pp. 1032-1038, 2008.

[17] S. A. Safavynia and L. H. Ting, "Long-latency muscle activity reflects continuous, delayed sensorimotor feedback of task-level and not joint-level error," *Journal of neurophysiology,* vol. 110, no. 6, pp. 1278-1290, 2013.

[18] D. B. Lockhart and L. H. Ting, "Optimal sensorimotor transformations for balance," *Nat Neurosci,* vol. 10, no. 10, pp. 1329-1336, 2007.

[19] S. A. Safavynia and L. H. Ting, "Sensorimotor feedback based on task-relevant error robustly predicts temporal recruitment and multidirectional tuning of muscle synergies," (in eng), *J Neurophysiol,* vol. 109, no. 1, pp. 31-45, Jan 2013, doi: 10.1152/jn.00684.2012.

[20] M. Afschrift, F. De Groote, and I. Jonkers, "Similar sensorimotor transformations control balance during standing and walking," *PLoS computational biology,* vol. 17, no. 6, p. e1008369, 2021.

[21] K. L. Jakubowski, Martino G, O. N. Beck, G. S. Sawicki, and L. H. Ting, "The intrinsic and neurally-mediated contributions to the balance correcting torque response differ between the ankle and hip," in *International Society of Biomechanics*, Fukuoka, Japan, 2023.

[22] K. L. Jakubowski, Martino G, G. S. Sawicki, and L. H. Ting, "Center of mass kinematics robustly predict reactive joint torques at the ankle, knee, and hip during perturbed standing," in *International Society of Biomechanics*, Fukuoka, Japan, 2023.

[23] S. L. Delp *et al.*, "OpenSim: open-source software to create and analyze dynamic simulations of movement," *IEEE transactions on biomedical engineering,* vol. 54, no. 11, pp. 1940-1950, 2007.

[24] P. W. Franks, G. M. Bryan, R. M. Martin, R. Reyes, A. C. Lakmazaheri, and S. H. Collins, "Comparing optimized exoskeleton assistance of the hip, knee, and ankle in single and multi-joint configurations," *Wearable Technologies,* vol. 2, p. e16, 2021.

[25] D. D. Molinaro, I. Kang, J. Camargo, M. C. Gombolay, and A. J. Young, "Subject-independent, biological hip moment estimation during multimodal overground ambulation using deep learning," *IEEE Transactions on Medical Robotics and Bionics,* vol. 4, no. 1, pp. 219-229, 2022.

[26] D. D. Molinaro, E. O. Park, and A. J. Young, "Anticipation and Delayed Estimation of Sagittal Plane Human Hip Moments using Deep Learning and a Robotic Hip Exoskeleton," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*, 2023: IEEE, pp. 12679-12685.

[27] R. L. Hybart and D. P. Ferris, "Embodiment for Robotic Lower-Limb Exoskeletons: A Narrative Review," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 2022.

[28] O. N. Beck, M. K. Shepherd, R. Rastogi, G. Martino, L. H. Ting, and G. S. Sawicki, "Exoskeletons need to react faster than physiological responses to improve standing balance," *Science Robotics,* vol. 8, no. 75, p. eadf1080, 2023.

[29] T. K. Uchida, A. Seth, S. Pouya, C. L. Dembia, J. L. Hicks, and S. L. Delp, "Simulating ideal assistive devices to reduce the metabolic cost of running," *PloS one,* vol. 11, no. 9, p. e0163417, 2016.