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A Predictive Framework to Provide Neuromuscular Insights in Reshaping Dynamic Balance during Transient Locomotion*

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***Abstract*—Anticipated and unanticipated directional changes are commonplace in daily lives. The need for dynamic balance is amplified when these transitions are performed in an unplanned (i.e., unanticipated) manner. In this study, we used predictive simulations and optimal control constructs to test a method for reshaping dynamic balance of unanticipated crossover cuts. We also compare how such improvements can be mediated at the musculotendon level. Our study shows that the performance of unanticipated crossover cuts can be optimized to improve dynamic balance, and highlight the potential for predictive simulations and optimal control to provide quantitative targets for reshaping dynamic balance in unanticipated crossover cuts—targets which are biologically-feasible.**

***Clinical Relevance*—This approach could inform task-specific rehabilitation therapy by suggesting how to reshape an individual's dynamic balance and which joint-level kinematic adjustments and muscle groups would be optimal to engage in doing so.**

I. Introduction

Anticipated and unanticipated changes of direction (i.e., locomotor transitions) are commonplace during our daily lives. The need for dynamic balance is amplified when the transition is performed with little to no prior knowledge of the future event [1], [2]. Among different maneuvers are crossover cuts which involve moving the trailing swing leg toward and in front of the leading stance leg. This style of transition increases the need for dynamic balance, relative to side-step cuts [1]. Individuals with mobility impairments or those that rely on the use of external assistive device such as lower-limb prostheses are especially challenged during these types of tasks. Thus, improving how specific individuals can perform these potentially devastating tasks could lead to fewer falls/injuries, inspire greater confidence in the use of assistive devices for ambulation, and inform targeted rehabilitation.

One technique to help guide this process is musculoskeletal modeling and predictive simulation [3]–[6]. Independent from existing experiment data, predictive musculoskeletal simulations based on biomechanically-meaningful objectives, can provide insights into novel human movements. For instance, Lin et al. predicted joint kinematics, muscle activations and knee contact loads by minimizing the metabolic energy cost during slow and fast walking [6]. Falisse et al. predicted realistic walking gaits of the healthy and the impaired by optimizing a multi-objective performance criterion that combines energy consumption and muscular efforts [4]. However, the efficacy of such simulations without a dynamic-balance performance objective may be undermined during devastating locomotor transitions, such as unanticipated crossover cuts. Nguyen et al. investigated human walking with a powered ankle exoskeleton by optimizing muscle activations and walking "stability" in the sense of base of support [5]. However, such stability criteria that neglects angular momentum may not accurately represent a person's dynamic balance during walking [7].

Whole-body angular momentum (H) is recently used for assessing dynamic balance as it is strictly regulated by human body during normal walking [8]. The regulation of H is important for maintaining dynamic balance because its time derivative equals to the net external moment about the body's center of mass. Previous studies have showed the close relationship between H and balance. For example, the magnitude of frontal-plane H during post-stroke walking has been correlated with worse clinical balance test scores [9]. The range of frontal-plane H of healthy individuals is greater during stair ascent walking that is thought more balance-challenged compared to level walking [10]. Furthermore, the regulation of H is achieved through muscle force generation [11], and it is useful to investigate how dynamic balance regulation can be improved through changes in coordination (i.e., changes in mechanical force of individual musculotendon units).

Dynamic optimization or optimal control, one approach to address the redundancy problem of human locomotion [3], [11], [12], can be used to solve predictive musculoskeletal simulations. Integrating forward dynamic simulation and optimization theory, dynamic optimization approach optimizes the muscle excitations to achieve specific biomechanical objectives of human walking. Computed muscle control also makes estimates of muscle forces by integrating static optimization and a linear feedback controller into muscle-driven forward simulations [13]. However, computed muscle control relies on inputs of experimental data and artificial residual forces, and cannot produce predictive movements required for balance improvement. Therefore, in this study, we used predictive simulations and optimal control constructs to test a method for reshaping dynamic balance of unanticipated crossover cuts. We also compare how such improvements can be mediated at the musculotendon level. We hypothesized that increased concentric and eccentric mechanical power of musculotendon actuators would be required for reshaping dynamic balance. Studies have previously identified anticipatory adjustments of dynamic balance that exist before transitions during anticipated cuts. Therefore, we expect the absence of these adjustments during

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unanticipated cuts must be compensated for through increased muscle force generation.

II. Methods

A. Experiment Data

Subject-specific as well as normative tracking data for this simulation approach was provided by a prior experiment [1], [14] of able-bodied subjects that performed unanticipated straight walking and 45° cutting tasks in response to random auditory cues, which was approved by the Institutional Review Board. The cue was given at the initiation of single-leg support of the leading leg (stance leg in a cut) before turning. Forty-two reflective markers were placed on human body and tracked by a 10-camera motion capture system (Motion Lab Systems, Baton Rouge, LA, USA) operating at 120 Hz. GRF data were captured at 1200 Hz using 6 force plates. Data were extracted and processed from the auditory cue to the next heel-strike of the leading leg, corresponding to roughly 1 stride that spanned each locomotor transition.

B. Musculoskeletal Model and Simulation

A musculoskeletal model (Fig. 1) of each participant was created in OpenSim 4.0 [15] by scaling the body segments in a generic model with 23 degrees of freedom and 92 Hill-type muscle-tendon actuators. The metatarsophalangeal joint was locked in each model. An inverse kinematics (IK) algorithm and a CMC algorithm [13] were performed in OpenSim to determine the initial guess for the dynamic optimization of simulations. Foot-ground interaction was modeled as Hunt-Crossley contact spheres under each foot.

For each subject, an optimal tracking simulation was performed at first using the results of CMC analysis as initial guess, and then the dynamic balance-reshape simulation was performed with the results of the optimal tracking simulation as initial guess. Both of the simulations were formulated as an optimal control problem [3], [12], as in

$$\min_{\boldsymbol{x},\boldsymbol{u}} J \tag{1-a}$$

$$\text{Subject to: } \dot{\boldsymbol{x}} = f(\boldsymbol{x}, \boldsymbol{u}, t) \tag{1-b}$$

$$\boldsymbol{x}_{lb} \le \boldsymbol{x}(t) \le \boldsymbol{x}_{ub} \tag{1-c}$$

$$\boldsymbol{u}_{lb} \le \boldsymbol{u}(t) \le \boldsymbol{u}_{ub} \tag{1-d}$$

where $\boldsymbol{x}$ is the state vector that includes generalized coordinates (joint angles), generalized velocities (joint velocities), muscle fiber length, and muscle activations; $\boldsymbol{u}$ is the control vector that represents muscle excitations; $\boldsymbol{x}_{lb}$ and $\boldsymbol{x}_{ub}$ are the lower and upper bound of the state vector; $\boldsymbol{u}_{lb}$ and $\boldsymbol{u}_{ub}$ are the lower and upper bound of the control vector; the state space equation represents the dynamics of the musculoskeletal model. The optimal control problem (1) were solved using direct collocation [3], [16] that transforms the optimal control problem to a large-scale nonlinear optimization problem. Customized MATLAB (Mathworks, Natick, MA, USA) code was written to solve the nonlinear optimization problem. This procedure resulted in a total of 10 simulations, which were analyzed, including two simulations for each participant (i.e., an optimal tracking simulation and a dynamic balance reshape simulation).

The objective function J for the optimal tracking simulations was as in [17]:

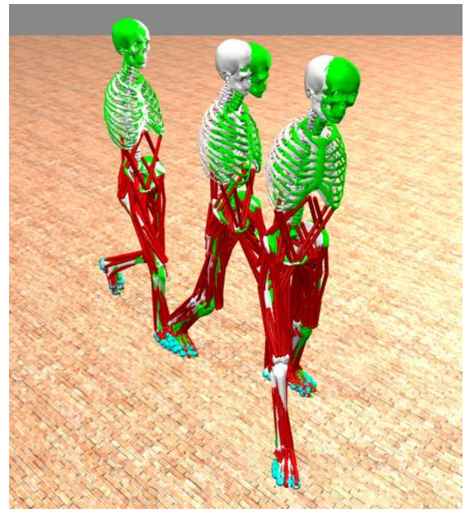

Figure 1. Visualized results of a dynamic balance-reshape (green) simulation and an optimal tracking (white) simulation of one subject at the start, middle and end of the locomotor transition, respectively. In this setting, leading (stance) leg is the right leg, and trailing leg is the left leg.

$$J = w \int_0^{t_f} (w_1 \|a\|_2^2 + w_2 \|\Delta GRF\|_2^2 + w_3 \left\|\Delta q_{pelv}\right\|_2^2) dt \tag{2}$$

where a is the muscle activation; ΔGRF is the tracking error of GRF; Δq_{pelv} is the tracking error of pelvic coordinates; w_i is weight coefficient and determined by experience. The objective function for balance-reshape simulations was as in

$$J = w \int_0^{t_f} \begin{array}{c} (w_1 \|a\|_2^2 + w_2 \|\Delta H\|_2^2 \\ + w_3 \left\|\Delta q_{pelv-xz}\right\|_2^2 + w_4 \left\|F_{penalty}\right\|_2^2) dt \end{array} \tag{3}$$

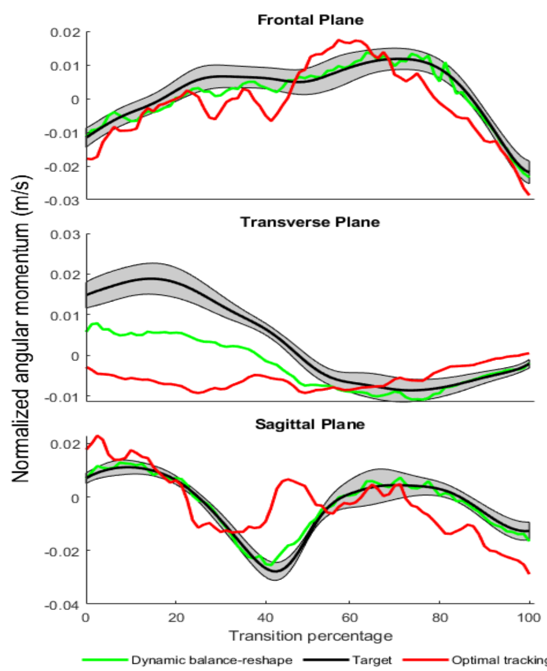

Figure 2. Average normalized whole-body angular momentum of experiment target (black), dynamic balance-reshape simulations (green) and optimal tracking simulations (red). Shaded area represents one standard deviation of experiment target angular momentum. Positive frontal, transverse and sagittal-plane angular momentum represents rotation away from the leading leg, toward the leading leg, and toward the posterior direction, respectively.

where ΔH is the reshaping error of whole-body angular momentum; $\Delta q_{pelv-xz}$ is the tracking error of pelvic horizontal translations that is used to guide the turning direction; $F_{penalty}$ is the contact force between two feet that is penalized to avoid segment penetration during movements. The target angular momentum is the group-averaged (except the simulated subject) experiment data of anticipated crossover cuts. The initial coordinates at t=0 were constrained tightly to simulate the initial unexpected state.

C. Statistical Comparisons

For these ten simulations, average positive and negative mechanical power of each musculotendon group was computed and then compared between tracking and reshaping simulations using one-tailed paired t-test (α=0.05).

III. Results

The optimal tracking simulation solutions closely matched the experiment data. The average root mean square error (RMSE) for GRF was less than 0.08 body weight, and the average RMSE for pelvic rotation and translation was less than 1.9˚ and 0.7 cm, respectively.

The dynamic balance-reshape simulations were able to adjust H of the unanticipated state toward that of the anticipated state (Fig. 2). In the frontal and sagittal planes, the reshaped H was inside one standard deviation range of the target experiment H except at around 35% and 45% of transition. In the transverse plane, the reshaped H was inside one standard deviation range of the target experiment H during the second half of transition. Although the reshaped transverse-plane H was outside one standard deviation range of the target experiment during the first half of transition, it more closely matched the experiment target H compared to the optimal tracking simulations.

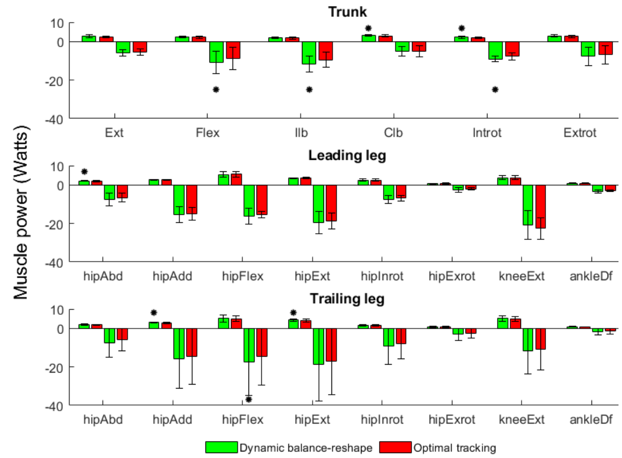

Figure 3. Average positive and negative musclulotendon actuator net power of each muscle group. “*” indicates significant different power in dynamic balance-reshape simulations compared to optimal-tracking simulations. “Ext”, “Flex”, “Ilb”, “Clb”, “Introt”, “Extrot”, “Abd”, “Add” and “Df” refer to extension, flexion, ipsilateral (toward leading-leg) bending, contralateral (toward trailing-leg) bending, interior rotation, exterior rotation, abduction, adduction and dorsiflexion, respectively. Positive (negative) mechanical power represents production (absorption) of power by the muscle actuator.

The average positive mechanical power of trunk contralateral (toward trailing-leg) bending muscles, trunk interior rotation muscles, leading-leg hip abductors, trailing-leg hip adductors and hip extensors was significantly larger in dynamic balance-reshape simulations compared to the tracking simulations (Fig. 3). The magnitude of average negative mechanical power of trunk flexors, trunk ipsilateral (toward leading-leg) bending muscles, trunk interior rotation muscles and trailing leg hip flexors was significantly larger in

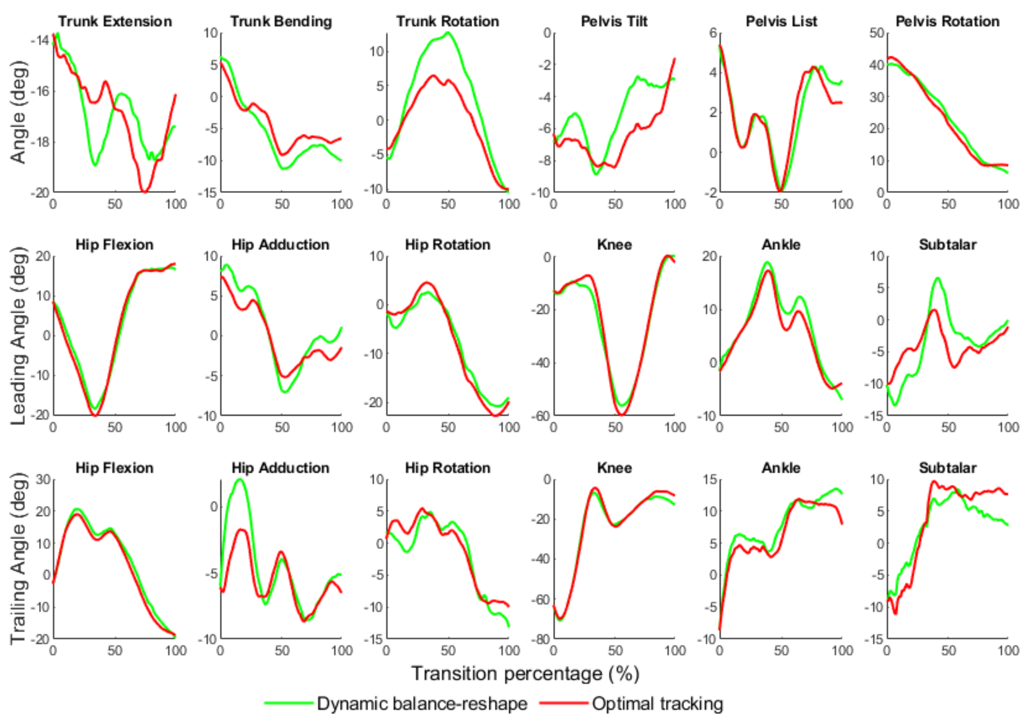

Figure 4. Average joint kinematics of trunk, pelvis, leading leg and trailing leg of dynamic balance-reshape simulations (green) and optimal-tracking simulations (red).

dynamic balance-reshape simulations relative to the tracking simulations.

In dynamic balance-reshape simulations, the average trunk extension angle decreased 2.6° at 35% and increased 1.6° at 75% of transition compared to the optimal tracking simulations (Fig. 4). The trunk bending decreased 2° at 50% of transition during reshape simulations. The trunk rotation angle increased 6.5° at about 50% of transition in reshape simulations relative to tracking simulations. In reshape simulations, the leading-leg hip adduction angle increased 3.2° and 2.2° at about 20% and 90% of transition, while the leading-leg hip rotation angle decreased 2.8° and 2.1° at 10% and 30% of transition. The trailing-leg hip adduction angle increased 3.8° at 20% of transition in reshape simulations.

IV. Discussion

In this study, we performed dynamic balance reshaping simulations and optimal tracking simulations of unanticipated crossover cuts to inform the movement of healthy subjects. Our results showed that whole-body dynamic balance during unanticipated crossover cuts can be reshaped as in anticipated states at least in the frontal and sagittal planes, as well as in the transverse plane during the second half of transition. Frontal and sagittal-plane dynamic balance in this reshape simulations was within one standard deviation of experiment target during most of the transition (Fig. 2). The decreased sagittal-plane dynamic balance from tracking to reshape simulations at about 40% of transition may be closely related to the decreased (more toward anterior direction) trunk extension (Fig. 3). This may suggest a way to mediate anteroposterior dynamic balance in unanticipated cuts through therapy training or using an assistive device [18] to target trunk extension. However, the increased (toward the trailing leg) trunk rotation was different from the increased transverse-plane dynamic balance in early reshape simulations. Instead, the increased (toward leading leg) trailing leg adduction may contribute to such enhanced transverse dynamic balance. The imperfect reshaping of transverse dynamic balance may be due to the incapability to further mediate trailing leg movement in the unanticipated condition. Furthermore, the adjustments of leading-leg adduction movement were in the same direction of frontal-plane dynamic balance, which may suggest it as a major contributor to regulating mediolateral dynamic balance during these movement.

Our hypothesis that increased mechanical power of muscle actuators would be required for reshaping dynamic balance was supported for selected muscle groups. The increased muscle power could also be related to the adjustment of joint kinematics during dynamic balance reshaping. For example, the increased positive net power of trunk contralateral bending muscles and negative power of trunk ipsilateral bending muscles in reshape simulations may contribute to the decreased trunk bending, suggesting that increased muscle power production may be required for frontal-plane dynamic balance reshaping. While the hip adduction angle increased in reshape simulations, the increased positive power of leading-leg hip abductors may act as a counterbalance to the influence of gravity to maintain dynamic balance [11]. In the trailing leg, the increased positive net power of hip adductors may contribute to the increased hip adduction angle during the early phase of these transitions.

These results demonstrate the potential to use a predictive simulation approach to inform task-specific as well as patient-specific rehabilitation therapies by suggesting how to reshape an individual's dynamic balance and identify which joint-level kinematic adjustments and muscle groups would be optimal to engage in doing so. Future work is required to investigate the feasibility of reshaping dynamic balance of patients, and to show that this numerical approach can be applied ubiquitously to multiple forms of ambulation.

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