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PREDICTIVE 3D MUSCULOSKELETAL SIMULATION OF A SINGLE STRIDE OF HUMAN RUNNING

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INTRODUCTION

Studies that investigate human locomotion traditionally rely on motion capture experiments to record marker trajectories and ground forces. These data are input into musculoskeletal models and analyses (e.g. inverse dynamics and static optimization [1]) or tracking simulations (e.g. computed muscle control [2]) are performed. This investigative paradigm is limited because it must be driven by experimental data and cannot predict kinematic adaptations caused by variations in the model (e.g. gait adaptation as a result of strengthening or weakening a muscle). On the other hand, forward simulations driven by control laws instead of experimental data can serve as a predictive paradigm. This predictive paradigm enables investigation of '*what-if*' questions, providing insight into how athletes may benefit from interventions such as optimizing strength training to deliver maximum athletic performance. Running has recently gained considerable attention in both the scientific press [1-3] and colloquial media, with specific regard to performance enhancement. Do artificial limbs yield performance benefits? Can gait re-training improve maximum running speed? Before predictive simulations can be used to explore such questions, it must first be shown that realistic human locomotion can be predicted. The aim of this study was to generate a predictive 3D muscle-driven simulation of running and assess the fidelity of the simulation by comparison to experimental data.

METHODS

The musculoskeletal model (Fig. 1) was actuated by 16 Hill-type musculotendon units (8 on each leg to actuator the ankle, knee, and hip in the sagittal plane), and 19 torque motors (to actuate the coronal and transverse plane of the lower limbs, and upper limbs). Physiologically accurate muscle models [4] and moment arms [5] were used in the whole body model (i.e., force-length-velocity curves and moment-arm-angle curves were based on experimental data). Feedback control laws [6,7] governed actuator excitations as each limb progressed through four states: first and second half of stance, and first and second half of swing (Table 1). Stance and swing transitions were based on the foot making and breaking contact with the ground, and inter-stance/inter-swing transitions were based on the sagittal plane distance between the ankle joint center and the model mass center [7]. Actuator control laws were grouped into three categories: force feedback, length feedback and proportional-derivative control (Table 1). A total of 118 design variables fully prescribed a simulation (85 for actuator controllers and 33 for initial conditions). Optimization was used to solve for these variables by parallelizing simulations across 95 CPU nodes (defined as a single iteration) using a Covariance Matrix Adaptation evolution strategy [8]. The main components of the objective function were: i) minimize metabolic energy across muscle actuators [5]; ii) minimize torque across joint actuators; and iii) achieve a target speed of 3.5 m/s without falling for as long as possible. We terminated the optimization after 5 days (~1500 iterations) and reported the first full gait cycle. For comparison, experimental data (n=9, 3.5 ± 0.12 m/s) from a previous study [1] were used to evaluate the predictive capacity of the optimization.

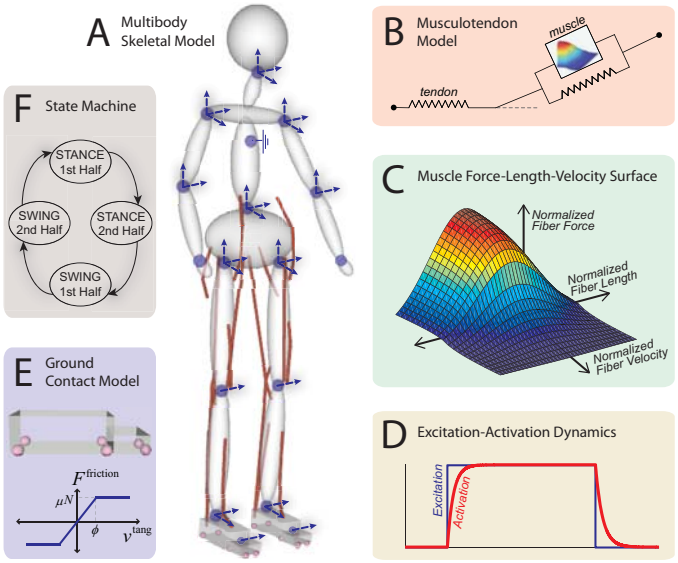

Figure 1: The predictive model implemented in OpenSim. The model had: [A] 36 degrees of freedom; and [B] 8 musculotendon actuators per leg, each bound by [C] force-length-velocity properties and [D] first order excitation-activation dynamics. [E] Ground contact was specified by 6 Hunt-Crossley spheres with Coulomb friction on each foot, with a stiffness of 2e7 N/m, coefficient of friction $\mu = 0.8$, and transition velocity $\phi = 0.005$ m/s. [F] Each limb progressed through a finite state machine, which determined the unique excitation control law for each actuator.

RESULTS AND DISCUSSION

The average model running speed across the gait cycle was 3.21 m/s. The simulation captured the basic features of running in the hip, knee, and ankle (Fig. 2), although the ankle was more plantarflexed than human runners during the flight phase. The recruitment of muscles in the predictive simulation were temporally consistent with experimental EMG data (Fig. 3, compare red and blue lines). Muscle forces in the predictive simulation had similar timing to those estimated with static optimization, though several muscles differed in magnitude (Fig. 3, red and black lines). Specifically, GAS, VAS and ILPSO developed higher peak forces, and GMAX developed peak force during terminal stance instead of terminal swing. HAMS developed greater force in stance than in swing, contrary to previous estimates [1]. TA was the muscle that most disagreed with EMG activity and is likely related to excessive ankle plantarflexion throughout the simulation. Differences in the quantitative muscle forces between our previous [1] and current solutions (Fig. 3) may be partially attributed to the two models differing in inertial properties, the number of muscles in the model, and moment arms.

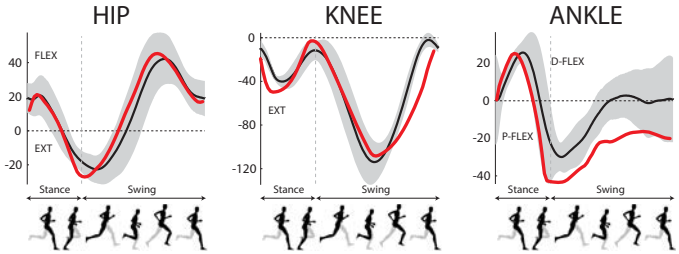

Figure 2: Sagittal plane joint kinematics of the lower limb (deg). Experimental results [1] (black, shaded area is 1 standard deviation) and model-predicted results (red).

Computational time limited the number of simulations that could be performed during the optimization. The successful stride simulated at ~40X slower than real time. We attribute this primarily to the stiff contact and Coulomb friction models used in foot-ground interaction (Fig 1E), which result in small integration steps and foot-slipping at low tangential velocities. We are improving the simulation by implementing a new constraint-based rigid contact algorithm that will eliminate foot-slipping and compliant contact stiffness. We believe this will reduce simulation times and allow a greater number of simulation iterations to be run so that we can converge to more human like kinematics. It should also provide the capability to optimize over multiple strides and at faster running speeds.

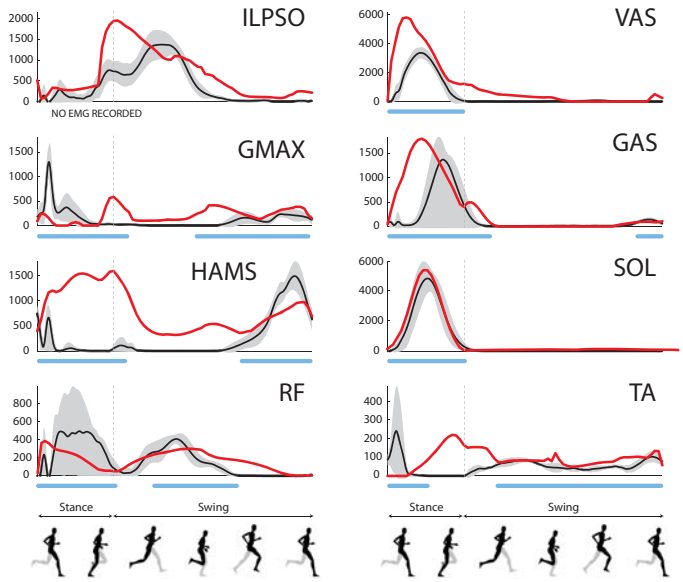

Figure 3: Muscle forces (N). Static optimization results [1] (black, shaded area is 1 std. dev.) and model-predicted (red). Blue lines indicate on-off patterns of experimental EMG [1].

CONCLUSIONS

The predictive optimization demonstrated here is a powerful tool that can capture the characteristics of human running in feasible time without experimental data. Implemented in OpenSim [1,2,4,9], it can take advantage of physiologically accurate muscle models and an accurate physics engine, and be distributed among a growing community. Our goal is to use the framework presented here to simulate faster running speeds and investigate the limitations of maximum sprinting in humans. We also aim to make '*what-if*' studies in musculoskeletal biomechanics more easily accessible by building the optimization infrastructure into OpenSim.

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Table 1: Control strategy for predictive model actuators. 85 controller design variables were optimized (torques: 29; muscles: 56).

Actuator	Control strategy used to compute actuator excitation			
	1'st half of STANCE	*2nd half of STANCE*	*1st half of SWING*	*2nd half of SWING*
Iliacus/Psoas (ILPSO)	PD control to maintain upright torso posture		stretch feedback (ILPSO)	PD control for sagittal hip
Gluteus Maximus (GMAX)	PD control to maintain upright torso posture		force feedback (GMAX)	PD control for sagittal hip
Biarticular Hamstrings (HAMS)	PD control to maintain upright torso posture		force feedback (HAMS)	
Rectus Femoris (RF)	constant control		constant control	
Vasti (VAS)	Force feedback (VAS) & P control for sagittal knee		constant control	PD control for sagittal knee
Gastrocnemius (GAS)	force feedback (GAS)		constant control	
Soleus (SOL)	force feedback (SOL)		constant control	
Tibialis Anterior (TA)	stretch feedback (TA) & force feedback (SOL)		stretch feedback (TA)	
Ideal Torque Actuators	PD control to achieve a target "stance phase" posture		PD control to achieve a target "swing phase" posture	