Predictive simulations of human walking produce realistic cost of transport at a range of speeds

Ong, Carmichael F. ; Geijtenbeek, Thomas; Hicks, Jennifer L.; Delp, Scott L.

Publication date
2017

Document Version
Final published version

Citation (APA)
Ong, C. F., Geijtenbeek, T., Hicks, J. L., & Delp, S. L. (2017). *Predictive simulations of human walking produce realistic cost of transport at a range of speeds*. 19-20. Abstract from 16th International Symposium on Computer Simulation in Biomechanics, Gold Coast, Australia.

PREDICTIVE SIMULATIONS OF HUMAN WALKING PRODUCE REALISTIC COST OF TRANSPORT AT A RANGE OF SPEEDS

Carmichael F. Ong[1], Thomas Geijtenbeek[2], Jennifer L. Hicks[1], and Scott L. Delp[1,3]

[1] Department of Bioengineering, Stanford University, Stanford, USA
[2] Department of Biomechatronics & Human-Machine Control, Delft University of Technology, Delft, NL
[3] Department of Mechanical Engineering, Stanford University, Stanford, USA
Email: ongcf@stanford.edu, Web: http://nmbl.stanford.edu

INTRODUCTION

Predictive simulations of human walking have great potential to expand our understanding of locomotion. For instance, they can isolate the effect of specific impairments on observed gait pathologies or aid in designing assistive devices by modeling human-device interactions. Introducing simulated impairments or adding augmentation devices to a model may change kinematics, including preferred walking speed. Experimental studies have characterized cost of transport over a wide range of walking speeds, and have shown that humans prefer walking at a speed that minimizes their cost of transport [1]. The purpose of this study was to use a predictive simulation framework to reproduce experimental energetic cost of transport. We trained a model to walk at speeds between 0.5 and 2.0 m/s and compared our simulated cost of transport to experimental data.

METHODS

We used a planar, 9-degree-of-freedom (dof) musculoskeletal model based on a model by Delp *et al*. [2]. The model (Fig. 1) included a 3-dof planar joint for the pelvis, and 1-dof hip, knee, and ankle joints in each leg. Each leg was actuated by 9 Hill-type musculotendon units using a compliant tendon, representing the major sagittal plane muscles. To better represent an average, healthy, young individual, we adjusted musculotendon parameters in our model based on a model by Rajagopal *et al*. [3]. Ligaments were modelled as variable stiffness springs that engaged during hyperextension and hyperflexion of the joints. Contact forces between the foot and the ground were computed using the Hunt-Crossley contact model [4], with contact spheres at the heels and toes to represent the foot and a contact plane to represent the ground. We modeled neural control using a series of state-based controllers based on the model developed by Geyer and Herr [5]. Briefly, this model uses a set of low-level controllers to calculate excitation for each muscle with a combination of constant signals, positive and negative feedback from the muscle length and force, and proportional-derivative (PD) controllers to stabilize pelvis orientation. A high-level controller determines when the low-level controllers are active based on the phase of gait. In this work, the high-level controller transitioned between 5 phases of gait: early stance, mid-stance, terminal stance, swing, and landing preparation. The controller was implemented in a custom software package.

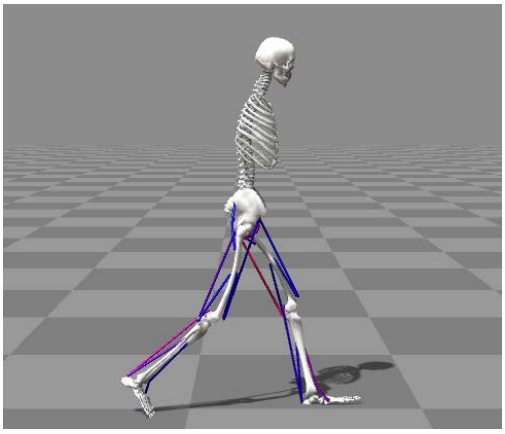

Fig 1: The model in double stance, training at a target speed of 1.25 m/s.

We generated a 10-second simulation using OpenSim version 3.3 [6], and then assessed performance using the following objective function, *J:*

$$J = J_{\mathrm{cot}} + w_{\mathrm{spd}} J_{\mathrm{spd}} + w_{\mathrm{inj}} J_{\mathrm{inj}} + w_{\mathrm{pel}} J_{\mathrm{pel}} + w_{\mathrm{hd}} J_{\mathrm{hd}}.$$

This function sought to minimize the gross cost of transport (J_{cot}) while maintaining a steady speed (J_{spd}), avoiding injury (J_{inj}), and stabilizing the upper body (J_{pel}, J_{hd}). We computed gross cost of transport, J_{cot}, by summing the basal and per-muscle metabolic rates [7, 8]. The speed penalty, J_{spd}, was applied if the speed averaged over a step differed from the target speed by more than 0.05 m/s. If the simulation

was terminated early due to the model falling, the speed was set to 0 m/s for the remainder of the 10 seconds, yielding a large penalty. The injury penalty, J_{inj}, discouraged hyperextension or hyperflexion of the joints by penalizing ligament use. To promote pelvis, trunk, and head stability, J_{pel} penalized large pelvic tilt deviation from a neutral position and zero rotation velocity, and J_{hd} penalized excessive accelerations of a point at the center of the head [9]. We manually adjusted weights (w_{spd}, w_{lig}, w_{pel}, w_{hd}) to balance these competing objectives.

We used the Covariance Matrix Adaptation Evolution Strategy algorithm [10] to solve for the controller and initial pose parameters that minimize our objective function, J. In total, there were 90 design variables: 70 variables for the gains and offsets in the muscle controllers, 16 variables for the initial position and velocities of the model, and 4 variables for the transition timing of the high-level controller. We used a population size (i.e., the number of function evaluations in each generation) of 16. Since this optimizer is stochastic, we ran the optimization 20 times for 3000 generations. The best solution was then used to seed another round of 20 optimizations. This was repeated until the change in the best objective function value decreased by less than 5% from the previous round's best value.

We optimized the model at speeds between 0.5 and 2.0 m/s, in 0.25 m/s increments. The model was first trained at 1.25 m/s. Each speed was trained by seeding with the solution from the neighboring speed (e.g., the solution for 1.25 m/s was used as the initial seed to train solutions for 1.00 and 1.50 m/s).

RESULTS AND DISCUSSION

Our model and optimization framework generated simulations that were in close agreement with experimental results [1, 11, 12] (Fig. 2). The minimum cost of transport from our simulations (3.17 J/kg·m) and the corresponding speed (1.23 m/s) were both within the range reported in previous experimental studies. Our cost of transport measures also captured realistic trends for decreasing and increasing speed, following the characteristic bowl-shaped curve. A steeper increase in cost of transport was observed while approaching slower speeds as compared with faster speeds. Since we used a planar model, future work is needed to determine energetic costs due to stabilization of and motion in the frontal and transverse planes.

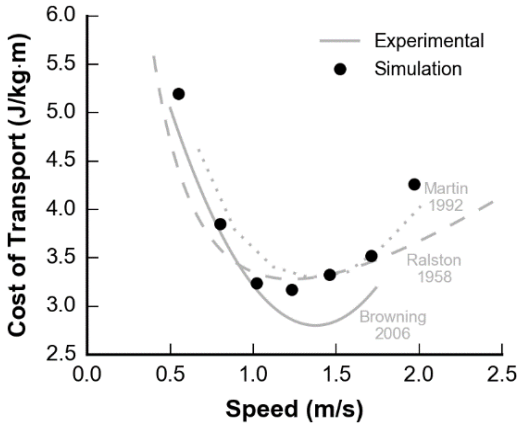

Fig 2: Comparison of measured cost of transport from three experimental studies (gray lines) with our simulated results (black dots).

CONCLUSIONS

Our finding that predictive simulations match experimental cost of transport data indicates that this method captures salient features of walking. This study increases confidence in the results of future simulations that study novel conditions, such as introducing musculoskeletal impairments or adding assistive devices.

REFERENCES

1. Ralston HJ, *Int Z Agnew Physiol* **17**: 277-283, 1958.
2. Delp SL, et al. *IEEE Trans Biomed Eng* **37**: 757-767, 1990.
3. Rajagopal, et al. *IEEE Trans Biomed Eng* **63**: 2068-2079, 2016.
4. Hunt KH, Crossley FRE, *ASME J Appl Mech* **42**: 440-445, 1975.
5. Geyer H, Herr H. *IEEE Trans Neural Syst Rehabil Eng* **18**: 263-273, 2010.
6. Delp SL, et al. *IEEE Trans Biomed Eng* **54**: 1940-1950, 2007.
7. Umberger BR, et al. *Comput Methods Biomech Biomed Eng* **6**: 99-111, 2003.
8. Uchida TK, et al. *PLoS ONE* **11**: e0163417, 2016.
9. Menz HB, et al. *Gait Posture* **18**: 35-46, 2003.
10. Hansen N, Kern S. Proc 8th Int Conf on PPSN: 282-291, 2004.
11. Martin PE, et al. *J Appl Physiol* **73**: 200-206, 1992.
12. Browning RC, et al. *J Appl Physiol* **100**: 390-398, 2006.

ACKNOWLEDGEMENTS

This work was supported by the National Center for Simulation in Rehabilitation Research (NCSRR) (NIH R24 HD065690) and the Mobilize Center for Mobility Data Integration to Insight (NIH U54 EB020405).