Improving Computed Muscle Control through Optimization to Generate Dynamic Simulations of Overground Running

Jeffrey A. Reinbolt[1] and Cyril J. Donnelly[2]
[1]Mechanical, Aerospace, & Biomedical Engineering, The University of Tennessee, Knoxville, USA
[2]School of Sport Science, Exercise and Health, The University of Western Australia, Perth, AU
Email: reinbolt@utk.edu

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1. Introduction

Numerical simulations are playing an increasingly important role in solving complex engineering problems, and have the potential to revolutionize medical decision making and treatment design. Musculoskeletal conditions cost the United States economy more than $849 billion per year (7.7% of the USA's GDP) and place great demands on the healthcare system [1]. Simulations enable engineers and clinicians to ask "what if" questions that investigate musculoskeletal conditions and treatment outcomes. Specifically, forward dynamic simulations give insight into the complex interaction between neuromuscular control, musculoskeletal geometry, and observed multijoint movements.

Computed muscle control is a popular choice to rapidly generate forward dynamic simulations [2]. This algorithm required a few minutes to determine muscle excitation patterns for a pedaling movement [2] and several minutes for a half-cycle of gait data [3]. Computed muscle control's speed and availability within OpenSim [4] have increased its popularity. Nearly 100 citations have been made to three main articles describing computed muscle control [2,3,4]. While some report computation time, most do not report two relevant numbers:

- Individual's time required to produce a *reasonable simulation* (e.g., closely tracking experimental kinematics and obeying Newton's equations of motion relating ground reactions and body segment accelerations).
- Quantitative *measures of unreasonability* (e.g., kinematic tracking errors and residual forces/torques needed to balance Newton's equations of motion – residuals are equivalent to experimental and modeling errors).

Given our experience developing the OpenSim software, using computed muscle control ourselves, and discussing its use with others, it takes an excessive amount of time for engineers or clinicians to produce a reasonable simulation. Depending on one's reasonability tolerance, it may take 1-3 days or up to a few months to produce one reasonable simulation. In all cases, individuals spend their time choosing an unnecessary number of input parameters for computed muscle control to generate a forward dynamic simulation that minimizes measures of unreasonability.

In this study, we used optimization to minimize measures of an unreasonable simulation by adjusting input parameters for computed muscle control. Our goal was to determine optimal input parameters that produce a simulation closely tracking experimental data of overground running with limited residual forces/torques. We hypothesized that the optimization would produce a simulation with smaller tracking errors, smaller residual forces/torques, and within less time compared with a simulation produce by an individual.

2. Methods

The subject analyzed in this study was from a set 34 male Western Australian Amateur Football players who had previously undergone movement analysis during anticipated and unanticipated sidestepping at The University of Western Australia, Perth, Australia [5]. Movement analysis data, including three-dimensional marker trajectories and ground reaction forces and moments, were collected as a routine part of the sidestepping study (Fig. 1a). The subject gave informed consent for the collection and analysis of his movement data. The data analysis included the creation of subject-specific dynamic simulations.

A three-dimensional, full-body, 37 degree-of-freedom (DOF) musculoskeletal model driven by 37 actuators formed the foundation of each simulation. The position and orientation of the pelvis relative to ground was defined with 6 DOFs. The head and torso were represented as a rigid segment connected with the pelvis by 3 DOFs. The remaining extremity joints were modeled as follows: each hip as 3 DOFs, each knee as 3 DOFs with its flexion/extension axis translating as a function of knee angle, each ankle as 1 DOF, each shoulder as 3 DOFs, each elbow and wrist as 2 DOFs. Each actuator was modeled as an ideal force or torque (handled the same as any other actuator, say a muscle-tendon unit, within the software). The model was generated in OpenSim and it was used in conjunction with movement analysis data to create a subject-specific dynamic simulation (Fig. 1b).

A dynamic simulation of the subject was created using a three-step process. First, the musculoskeletal model was scaled to represent the experimentally measured size of the subject. Second, inverse kinematics analysis was utilized to obtain values of generalized coordinates for the model that closely matched the experimentally measured kinematics of the subject. Third, computed muscle control was implemented to determine an optimal set of actuator excitations that produced a forward dynamic simulation generally consistent with the experimentally measured kinematics. This three-step process was used to create simulations of the subject during overground running from pre-contact to toe-off of the right limb.

While optimization procedures were used during every step, the third step involving computed muscle control was improved by a nested, or two-level, optimization approach (Fig. 1c). The inner-level optimization generated a simulation using computed muscle control and its associated input parameters including acceleration tracking weights, maximum residual forces/torques, and maximum joint torques. The outer-level optimization chose these input parameters that produced a simulation minimizing measures of unreasonability.

An inner-level optimization was used by computed muscle control to generate a simulation. The inner-level cost function was the default OpenSim implementation. This inner-level cost function (1) minimized weighted ($w_{\ddot{q}_i}$) squared error between desired acceleration ($\ddot{q}_i^{desired}$) and forward dynamically simulated acceleration ($\ddot{q}_i^{simulated}$)

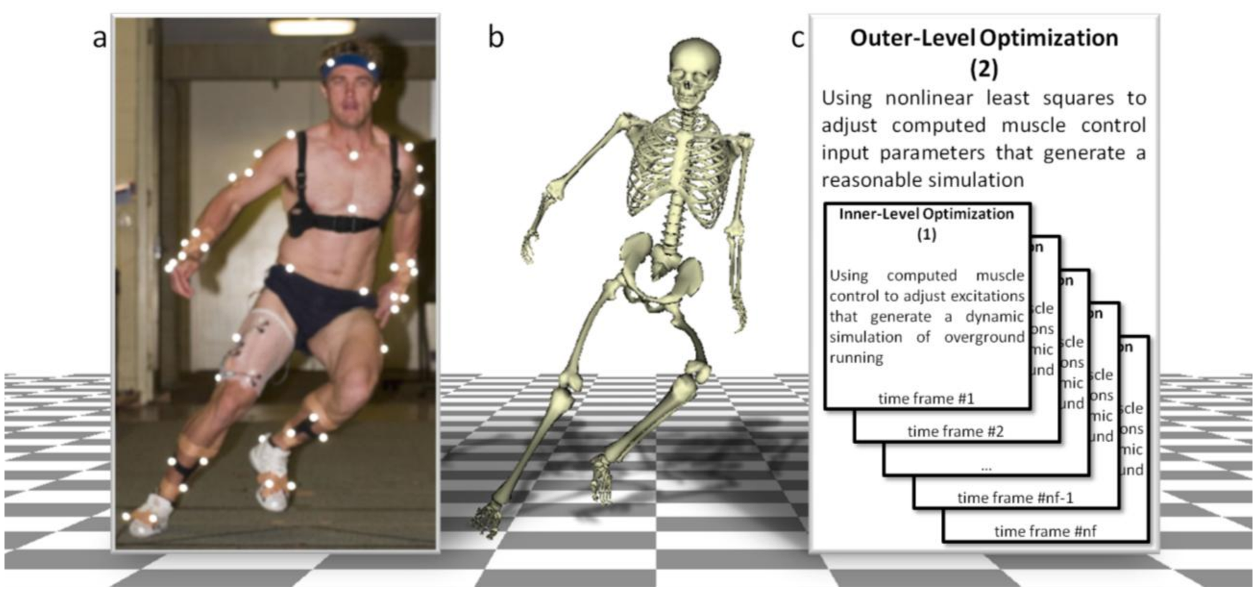

Figure 1. The subject in this study was a male Western Australian Amateur Football player. (a) Movement analysis data, including three-dimensional marker trajectories and ground reaction forces and moments, were collected for overground running. (b) A dynamic simulation of the subject was created using a three-step process: 1) a 37 degree-of-freedom musculoskeletal model with driven by 37 actuators was scaled to the subject's size; 2) inverse kinematics determined values of the model's generalized coordinates that matched marker data; and 3) computed muscle control determine an optimal set of excitations that produced a forward dynamic simulation. (c) An outer-level optimization determined input parameters for computed muscle control that were used during the inner-level optimization to generate a reasonable forward dynamic simulation of overground running.

over nq DOFs, squared residual force/torque (R_j) proportional to its driving excitation (x_j^R) normalized by its maximum (R_j^{max}) over 6 residuals, and squared joint torque (T_k) proportional to its driving excitation (x_k^T) normalized by its maximum (T_k^{max}) over nT torques:

$$\min_{\boldsymbol{x}^R,\ \boldsymbol{x}^T} \left[\sum_{i=1}^{nq} w_{\ddot{q}_i} \left(\ddot{q}_i^{desired} - \ddot{q}_i^{simulated} \right)^2 + \sum_{j=1}^{6} \left(\frac{R_j(x_j^R)}{R_j^{max}} \right)^2 + \sum_{k=1}^{nT} \left(\frac{T_k(x_k^T)}{T_k^{max}} \right)^2 \right] \Bigg|_{inner-level} \quad (1)$$

The design variables were a set of excitations ($\boldsymbol{x}^R$, $\boldsymbol{x}^T$) driving each residual force/torque or joint torque actuator. These excitations were input into the forward dynamic model and numerical integration of Newton's equations of motion generated the dynamic simulation for every time frame. The simulation output kinematics, residual forces/torques, and joint torques that were based on the choice of input parameters including each acceleration weight ($w_{\ddot{q}_i}$), maximum residual (R_j^{max}), and maximum joint torque (T_k^{max}). The input parameter choices for computed muscle control determine whether or not the dynamic simulation closely tracks experimental kinematics data with limited residual forces/torques, producing a reasonable simulation.

An outer-level optimization, rather than human intuition, was used to determine input parameters that generated a reasonable simulation. The outer-level cost function reduced the number of human-defined input parameters from $nq + 6 + nT$ (74 for our model) to merely 2. The outer-level cost function (2) minimized uniformly weighted (W_{pelvis}, 1000 in our case) squared error between experimental kinematics (q_{ij}^{exp}) and simulated kinematics (q_{ij}^{sim}) over 6 pelvis DOFs, squared error for kinematics over the remaining nq DOFs, uniformly weighted (W_R, 500 in our case) squared residual force/torque (R_{ik}) over 6 residuals, and squared joint torque (T_{il}) over nT torques with each quantity taken over nf time frames:

$$\min_{\boldsymbol{w}_{\ddot{q}},\ \boldsymbol{R}^{max},\ \boldsymbol{T}^{max}} \sum_{i=1}^{nf} \left[W_{pelvis} \sum_{j=1}^{6} \left(q_{ij}^{exp} - q_{ij}^{sim} \right)^2 + \sum_{j=7}^{nq} \left(q_{ij}^{exp} - q_{ij}^{sim} \right)^2 + W_R \sum_{k=1}^{6} {R_{ik}}^2 + \sum_{l=1}^{nT} {T_{il}}^2 \right] \Bigg|_{outer-level} \quad (2)$$

The design variables were a set of acceleration weights ($\boldsymbol{w}_{\ddot{q}}$), maximum residual forces/torques ($\boldsymbol{R}^{max}$), and maximum joint torques ($\boldsymbol{T}^{max}$) defining input parameters for computed muscle control. These input parameters were used throughout the inner-level optimization to generate a dynamic simulation closely tracking experimental kinematics data with limited residual forces/torques.

We evaluated our hypothesis regarding the tracking errors, residual forces/torques, and total time by comparing these quantities from the optimization to those produced by the individual.

3. Results and Discussion

Optimal input parameters for computed muscle control were found (Fig. 2) that produced a simulation closely tracking experimental data (RMS errors less than 3.9º for hip internal rotation of the swing limb) of overground running with limited residual forces (RMS less than 0.3N) and torques (RMS less than 0.4Nm). When comparing the optimized simulation with that produced by the individual, the RMS tracking errors increased at most 3.1º (again for hip internal rotation of the swing limb). In some DOFs, the RMS tracking errors decreased slightly (2.9mm for vertical position of the pelvis). These tracking error changes were due to the fact that the residual forces/torques decreased significantly (RMS up to 151N and 23Nm). As for total time required to generate each simulation, the individual spent approximately 3 research days on the problem and the optimization required a wall clock time of 11.8 hours (approximately a 50% decrease in recorded time; however, the optimization allows the individual to focus on other research while it is running, which magnifies this difference in recorded time).

We did not expect the large increase (< 3.1º) in tracking errors and we were surprised by the differences (< 15Nm) in joint torques. Both changes were necessary to dramatically reduce the residual forces/torques. The magnitudes of these changes were determined by our weight choices for tracking pelvis DOFs ($W_{pelvis} = 1000$) and reducing residual forces/torques ($W_R = 500$). Given a smaller weight values, the outer-level cost function would be minimized differently and emphasis would be placed on tracking errors other than the pelvis and reducing joint torques.

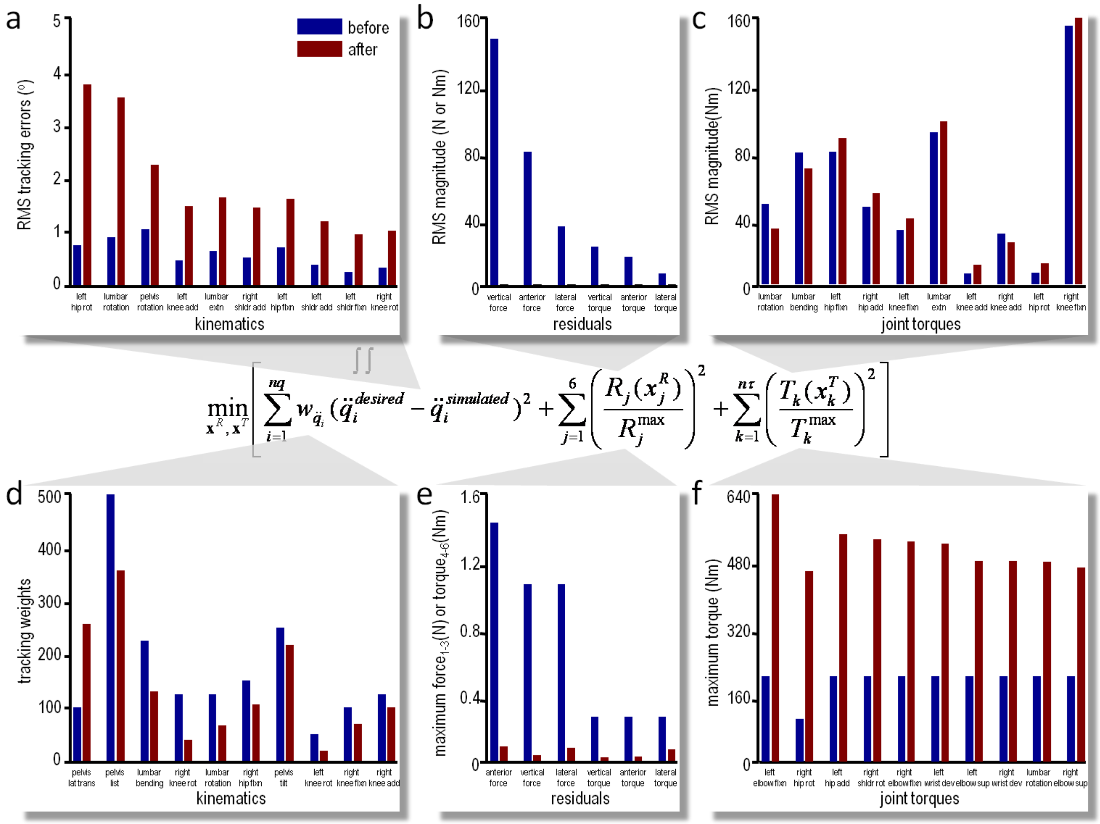

Figure 2. Largest differences ordered by decreasing magnitude for (a) kinematics, (b) residual forces/torques, and (c) joint torques resulting from simulations generated using computed muscle control before (blue, by the individual) and after (red) optimization. These results are based on input (d) acceleration weights, (e) maximum residual forces/torques, and (f) maximum joint torques chosen by the individual (before case) or the optimizer (after case).

Improving computed muscle control through optimization allows engineers and clinicians to produce a reasonable forward dynamic simulation within a modest amount of time and without the need to choose extra input parameters.

4. Acknowledgments

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