SIMULATION OF GAIT USING A 3D MUSCULOSKELETAL MODEL

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INTRODUCTION

Predictive simulation of gait has many applications ranging from the design of assistive devices to the planning of surgical interventions. Unfortunately, the traditional method to solve the resulting optimal control problem, the shooting method, is computationally very expensive. This, associated with the high complexity of current models of the musculoskeletal system, prevents the wider use of predictive simulation of gait in clinical applications. For instance, Anderson and Pandy (2001) reported a computational time of 10000 hours to simulate gait for a 3D model using the shooting method [1].

Direct collocation (DC) has been proposed as a computationally more efficient alternative to the shooting method [2]. We have shown that DC is particularly suited to solve the two point boundary value problem arising from the periodicity constraints in gait using a 2D musculoskeletal model [3]. In this paper we assess the accuracy and computational efficiency of DC when used to simulate gait with a state of the art 3D model.

METHODS

The 3D musculoskeletal model was adapted from [4] and consisted of 8 segments (pelvis, thighs, shanks, feet and wobbling trunk mass) actuated by 86 Hill-type muscle models. Foot-ground contact was modeled by 92 elements distributed over the foot sole with nonlinear spring-damper properties and friction. The model has 214 states $\boldsymbol{x}$ (generalized coordinates and velocities, muscle contractile element lengths and muscle activations) and 86 controls $\boldsymbol{u}$ (muscle excitations).

The optimal control problem was formulated as: for a given gait speed v find trajectories $\boldsymbol{x}(t)$ and $\boldsymbol{u}(t)$ and stride period T that minimize a cost function J subject to constraints due to system dynamics

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x},\boldsymbol{u}) \tag{1}$$

and periodicity

$$\boldsymbol{x}(T) = \boldsymbol{x}(0) + vT\ \hat{\boldsymbol{x}}, \qquad \boldsymbol{u}(T) = \boldsymbol{u}(0), \tag{2}$$

where $\hat{\boldsymbol{x}}$ is the state space unit vector for forward translation.

The optimal control problem was transformed into a Nonlinear Programming Problem (NLP) using direct collocation [5]. Unknowns were T and states and controls at each node k. System dynamics was discretized using the trapezoidal scheme as

$$\frac{\boldsymbol{x}_{k+1} - \boldsymbol{x}_k}{t_{k+1} - t_k} = \frac{\boldsymbol{f}(\boldsymbol{x}_k,\boldsymbol{u}_k) + \boldsymbol{f}(\boldsymbol{x}_{k+1},\boldsymbol{u}_{k+1})}{2}. \tag{3}$$

The method was evaluated on a tracking problem, with cost function consisted of two terms, the first measuring the “distance” between simulated and normative, experimental data, and the second measuring muscle “effort”:

$$J = \frac{1}{m(n-1)} \sum_{j=1,k=1}^{m,n-1} \left(\frac{y_{j,k} - \bar{y}_{j,k}}{\sigma_{j,k}} \right)^2 + w \sum_{i=1,k=1}^{86,n-1} \frac{V_i a_{i,k}^2}{V(n-1)} \tag{4}$$

where n is the number of nodes, a is the muscle activation, V is the muscle volume, $\bar{y}$ is reference experimental data (vertical, medial-lateral and posterior-anterior ground reaction forces, position of the pelvis CM and hip, knee and ankle angles), y is the corresponding simulated quantity, σ is a corresponding scaling factor, m is the number of states and grfs considered in the first term, and w is a weight factor.

A walking speed of 1.1m/s was imposed, bilateral symmetry was assumed, and the weight factor in (4) was set to w=1. The NLP was solved by using SNOPT (tomopt.com/tomlab), a sparse sequential quadratic programming solver. The primordial initial guess was obtained by successive unconstrained optimizations where a term was added to the cost function (4) containing the mean squares of the dynamic constraint violations (3) multiplied by a weight factor. The weight factor was gradually increased until dynamic constraints’ violations were small enough to allow convergence of the dynamically constrained optimization.

Accuracy was first assessed by mesh refinement, with solutions obtained for 25, 50 and 100 nodes. For further validation, the initial conditions and states from the DC solutions were used as inputs for conventional integration with variable integration step (Matlab ODE23), and results were compared.

RESULTS AND DISCUSSION

Figure 1 shows the solution for three representative variables, right vertical ground reaction force, right hip flexion and right Soleus activation for the three mesh densities. All DC solutions are very similar while the 50-node and the 100-node solutions are virtually identical, which is also indicated by the very similar values of the corresponding optimal cost function values (Tab.1).

The comparison with forward integration results (red lines in Fig.1) shows a significant divergence for the 25-node solution, a small one for the 50-node solution and an excellent agreement between the 100-node DC solution and the corresponding forward integration results. This is also illustrated by the decreasing differences at the end of the simulation as the mesh is refined (Tab.1). The comparison shows that an accurate solution in terms of agreement with forward integration results (100-node solution) can be reproduced using much coarser meshes (50 or even 25 nodes). It also indicates that a 50-node discretization is probably appropriate for most simulations using this model.

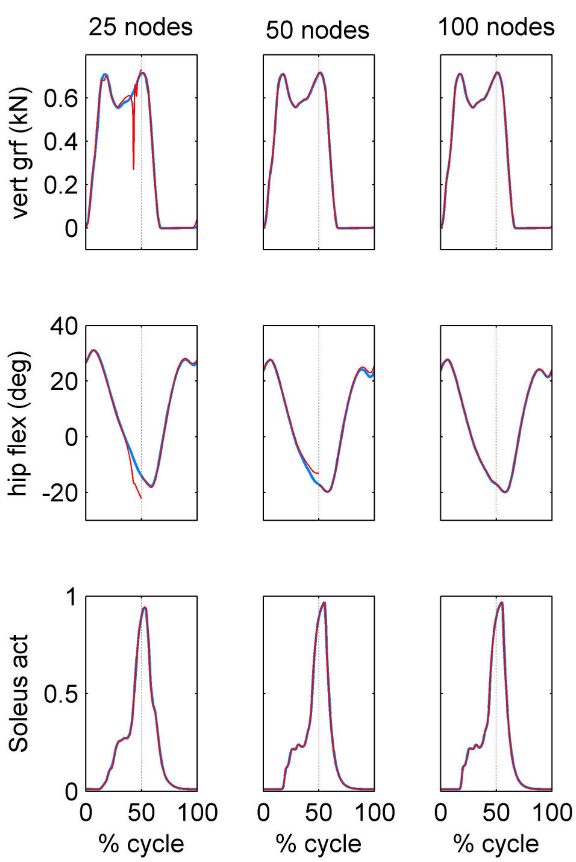

Figure 1: Blue curves are solutions using DC and 3 different mesh densities, 25, 50 and 100 nodes. Red lines are the corresponding results of forward integration using the neural excitations and initial conditions from the DC solutions.

The computation time, including the generation of a feasible initial guess and multiple restarts of the optimizations, was in the order of one week on a personal computer. This compares very favorably to the computational cost reported in other predictive gait simulation studies, most remarkably to the 10000 hours in [1], which used the shooting method and a musculoskeletal model of similar complexity.

This study shows that direct collocation is an accurate and computationally more efficient alternative to other methods for predictive simulation of gait using realistic, complex musculoskeletal models. While we tested our algorithms on a tracking problem, we expect similar performance on predictive gait optimizations, based on experience with 2D models [3].

Table 1: cost function value J and mean of absolute differences at the end of the simulation between the DC solution $\boldsymbol{x}$(T/2) and the forward integration result $\boldsymbol{x}^{i}$(T/2).

nodes	*cost function* (J)	*mean* $\lvert \boldsymbol{x}(T/2) - \boldsymbol{x}^{i}(T/2) \rvert$
25	0.1552	0.047
50	0.0974	0.016
100	0.0973	0.004

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