CREATION OF PATIENT-SPECIFIC DYNAMIC MODELS FROM THREE-DIMENSIONAL MOVEMENT DATA USING OPTIMIZATION

[1]Jeffrey A. Reinbolt and [1,2]Benjamin J. Fregly

[1]Department of Mechanical & Aerospace Engineering, University of Florida, Gainesville, FL
[2]Department of Biomedical Engineering, University of Florida, Gainesville, FL
Email: *fregly@ufl.edu*; Web: *www.mae.ufl.edu/~fregly*

INTRODUCTION

Forward and inverse dynamics analyses of gait can be used to study clinical problems in neural control, rehabilitation, orthopedics, and sports medicine. These analyses utilize a dynamic skeletal model that requires values for joint parameters (JPs - joint positions and orientations in the body segments) and body segment parameters (BSPs - masses, mass centers, and moments of inertia of the body segments). If the specified parameter values do not match the patient's anatomy and mass distribution, then the predicted gait motions and loads may not be indicative of the clinical situation.

The literature contains a variety of methods to estimate JP and BSP values on a patient-specific basis. Anatomic landmark methods estimate parameter values using scaling rules developed from cadaver studies [1,2,3,4]. In contrast, optimization methods adjust parameter values to minimize errors between model predictions and experimental measurements. Optimization of JP values for three-dimensional (3D) multi-joint kinematic models can have a high computational cost [5]. Optimization of BSP values without corresponding optimization of JP values has been performed with limited success for planar models of running, jumping, and kicking motions [6].

This study presents a computationally-efficient two-phase optimization approach for determining patient-specific JP and BSP values in a dynamic skeletal model given experimental movement data to match. The first phase determines JP values that best match experimental kinematic data, while the second phase determines BSP values that best match experimental kinetic data. The approach is demonstrated by fitting a 3D, 27 degree-of-freedom (DOF), parametric full-body gait model possessing 98 JPs and 84 BSPs to synthetic (i.e., computer generated) and experimental movement data.

METHODS

A sample dynamic model is needed to demonstrate the proposed two-phase optimization approach. For this purpose, we use a parametric 3D, 27 DOF, parametric full-body gait model whose equations of motion were derived with the symbolic manipulation software, Autolev™ (OnLine Dynamics, Sunnyvale, CA) [5]. The pelvis was connected to ground via a 6 DOF joint and the remaining 13 segments comprised four open chains branching from the pelvis. The positions and orientations of joint axes within adjacent segment coordinate systems were defined by unique JPs. The segment masses, mass centers, and moments of inertia were described by unique BSPs. Anatomic landmark methods were used to estimate nominal values for 7 BSPs per segment [4] and 6 hip [1], 9 knee [2], and 12 ankle [3] JPs.

Experimental kinematic and kinetic data were collected from a single subject using a video-based motion analysis system (Motion Analysis Corporation, Santa Rosa, CA) and two force plates (AMTI, Watertown, MA). Institutional review board approval and informed consent were obtained prior to the experiments. Segment coordinate systems were created from surface marker locations measured during a static standing pose. Unloaded isolated joint motions were performed to exercise the primary functional axes of each lower extremity joint (hip, knee, and ankle on each side). Gait motion and ground reaction data were collected to investigate simultaneous motion of all lower extremity joints under load-bearing physiological conditions.

To evaluate the optimization methodology, we generated two types of synthetic movement data from the experimental data sets. The first type was noiseless synthetic data generated by moving the model through motions representative of the isolated joint and gait experiments. The second type was synthetic data with superimposed numerical noise to simulate skin and soft tissue movement artifacts. A continuous noise model of the form $A\sin(\omega t+\varphi)$ was used with the following uniform random parameter values: amplitude A (0 to 1 cm); frequency ω (0 to 25 rad/s), and phase angle φ (0 to 2π) [7].

The first phase of the optimization procedure adjusted JP values and model motion to minimize errors between model and experimental marker locations (Eq. 1). For isolated joint motion trials, the design variables were 540 B-spline nodes ($\boldsymbol{q}$) parameterizing the generalized coordinate trajectories (20 nodes per DOF) and 6 hip, 9 knee, or 12 ankle JPs ($\boldsymbol{p}_{JP}$). For the gait trial, the number of JPs was reduced to 4 hip, 9 knee, and 4 ankle, due to inaccuracies in determining joint functional axes with rotations less than 25° [8]. The initial value for each B-spline node and JP was chosen to be zero to test the robustness of the optimization approach. The JP cost function (e_{JP}) minimized the errors between model (m') and experimental (m) marker locations for each of the 3 marker coordinates over nm markers and nf time frames. The JP optimizations were performed with Matlab's nonlinear least squares algorithm (The Mathworks, Natick, MA).

$$e_{JP} = \min_{\boldsymbol{p}_{JP},\boldsymbol{q}} \sum_{i=1}^{nf}\sum_{j=1}^{nm}\sum_{k=1}^{3}\left[m_{ijk} - m'_{ijk}(\boldsymbol{p}_{JP},\boldsymbol{q}) \right]^2 \qquad (1)$$

The second phase of the optimization procedure adjusted BSP values to minimize the residual forces and torques acting on a 6 DOF ground-to-pelvis joint (Eq. 2). Only the gait trial was used in this phase. The design variables for phase two were a reduced set of 20 BSPs ($\boldsymbol{p}_{BSP}$ – 7 masses, 8 centers of mass, and 5 moments of inertia) accounting for body symmetry and limited joint ranges of motion during gait. The initial seed for each BSP was the nominal value or a randomly altered value within ± 50% of nominal. The BSP cost function (e_{BSP}) utilized a combination of pelvis residual loads (F and T)

calculated over all nf time frames and differences between initial ($\boldsymbol{p'}_{BSP}$) and current ($\boldsymbol{p}_{BSP}$) BSP values. The residual pelvis forces (F) were normalized by body weight (BW) and the residual pelvis torques (T) by body weight times height ($BW*HT$). BSP differences were normalized by their respective initial values to create nondimensional errors. The BSP optimizations were also performed with Matlab's nonlinear least squares algorithm. Once a BSP optimization converged, the final BSP values were used as the initial guess for a subsequent BSP optimization, with this processing being repeated until the resulting pelvis residual loads converged.

$$e_{BSP} = \min_{\boldsymbol{p}_{BSP}} \sum_{i=1}^{nf} \sum_{j=1}^{3} \left\{ \left[\frac{F_{ij}(\boldsymbol{p}_{BSP})}{BW} \right]^2 + \left[\frac{T_{ij}(\boldsymbol{p}_{BSP})}{BW*HT} \right]^2 \right\} + \left(\frac{\boldsymbol{p}_{BSP} - \boldsymbol{p'}_{BSP}}{\boldsymbol{p'}_{BSP}} \right)^2 \quad (2)$$

The JP and BSP optimization procedures were applied to all three data sets (i.e., synthetic data without noise, synthetic data with noise, and experimental data). For isolated joint motion trials, JPs for each joint were optimized separately. For comparison, JPs for all three joints were optimized simultaneously for the gait trial. Subsequently, BSPs were optimized for the gait trial using the previously optimized JP values. Root-mean-square (RMS) errors between original and recovered parameters, marker distances, and pelvis residual loads were used to quantify the procedure's performance. All optimizations were performed on a 3.4 GHz Pentium 4 PC.

RESULTS AND DISCUSSION

For phase one, each JP optimization using noiseless synthetic data precisely recovered the original marker trajectories and model parameters to within an arbitrarily tight convergence tolerance (Table 1). For the other two data sets, RMS marker distance errors were at most 8.59 mm (synthetic with noise) and 6.72 mm (experimental), which are of the same order of magnitude as the amplitude of the applied continuous noise model. Optimizations of the two synthetic data sets required between 13 and 43 seconds of CPU time while the experimental data sets required between 231 and 616 seconds of CPU time. These computation times were orders of magnitude faster than those reported in [5] using a different optimization procedure.

For phase two, each BSP optimization using noiseless synthetic data produced zero pelvis residual loads and recovered the original BSP values to within an arbitrarily tight convergence tolerance (Table 2). For the other two data sets, pelvis residual loads and BSP errors remained small, with a random initial seed producing nearly the same pelvis residual loads but slightly higher BSP errors than when the correct initial seed was used. Required CPU time ranged from 11 to 48 seconds.

CONCLUSIONS

This study presented a two-phased optimization approach for tuning joint and body segment parameters in a dynamic skeletal model to match experimental movement data from a specific patient. For the full-body gait model used in this study, the JP optimization satisfactorily reproduced patient-specific JP values while the BSP optimization successfully reduced pelvis residual loads while allowing variation in the BSP values away from their initial guesses. The JP and BSP values found by this two-phase optimization approach are only as reliable as the noisy experimental movement data used as inputs. By optimizing over all time frames simultaneously, the procedure smoothes out the effects of this noise. An optimization approach that modifies JPs and BSPs simultaneously may provide even further reductions in pelvis residual loads.

REFERENCES

1. Bell AL, et al. *J Biomech* **23**, 617-621, 1990.
2. Churchill DL, et al. *Clin Orth Rel Res* **356**, 111-118, 1998.
3. Inman VT. *The Joints of the Ankle*. Williams and Wilkins Co., Baltimore, MD, 1976.
4. de Leva P. *J Biomech* **29**, 1223-1230, 1996.
5. Reinbolt JA, et al. *J Biomech* **38**, 621-626, 2005.
6. Vaughan CL, et al. *J Biomech Eng* **104**, 38-44, 1982.
7. Chèze L, et al. *J Biomech* **28**, 879-884, 1995.
8. Chèze L, et al. *Hum Mov Sc* **17**, 1-15, 1998.

ACKNOWLEDGEMENTS

This study was funded by Whitaker Foundation and NIH National Library of Medicine (R03 LM07332) grants to B.J.F.

Table 1: Summary of RMS marker distance and joint parameter errors produced by phase one of the optimization.

Movement data	RMS error	Ankle	Knee	Hip	Full leg
Synthetic without noise	Marker distance (mm)	3.34e-04	6.44e-04	1.43e-04	3.23e-04
	Orientation parameter (deg)	1.47e-03	5.85e-04	n/a	6.88e-06
	Position parameter (mm)	4.16e-04	1.48e-03	5.93e-05	2.91e-05
Synthetic with noise	Marker distance (mm)	8.26	6.16	8.59	5.49
	Orientation parameter (deg)	0.836	0.127	n/a	0.157
	Position parameter (mm)	3.76	1.15	0.845	2.35
Experimental	Marker distance (mm)	3.21	3.57	4.38	6.72

Table 2: Summary of RMS pelvis residual load and body segment parameter errors produced by phase two of the optimization.

Movement data	RMS error				
	Force (N)	Torque (N·m)	Inertia (kg·m^2)	Mass (kg)	Center of mass (m)
Synthetic without noise	2.12e-11	4.54e-11	7.27e-10	2.23e-08	2.35e-09
Synthetic with noise (correct initial seed)	15.91	5.55	4.13e-04	0.858	6.56e-03
Synthetic with noise (random initial seed – 10 cases)	15.90 $\pm$ 0.21	5.62 $\pm$ 0.182	1.78e-02 $\pm$ 6.82e-03	1.49 $\pm$ 0.44	3.46e-02 $\pm$ 7.96e-03
Experimental	35.33	14.71	n/a	n/a	n/a