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Short communication

Determination of patient-specific multi-joint kinematic models through two-level optimization

Jeffrey A. Reinbolt[a,b], Jaco F. Schutte[b], Benjamin J. Fregly[a,b,*], Byung Il Koh[c], Raphael T. Haftka[b], Alan D. George[c], Kim H. Mitchell[d]

[a] *Department of Biomedical Engineering, University of Florida, Gainesville, FL, USA*
[b] *Department of Mechanical & Aerospace Engineering, University of Florida, Gainesville, FL, USA*
[c] *Department of Electrical & Computer Engineering, University of Florida, Gainesville, FL, USA*
[d] *The Biomotion Foundation, West Palm Beach, FL, USA*

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Abstract

Dynamic patient-specific musculoskeletal models have great potential for addressing clinical problems in orthopedics and rehabilitation. However, their predictive capability is limited by how well the underlying kinematic model matches the patient's structure. This study presents a general two-level optimization procedure for tuning any multi-joint kinematic model to a patient's experimental movement data. An outer level optimization modifies the model's parameters (joint position and orientations) while repeated inner level optimizations modify the model's degrees of freedom given the current parameters, with the goal of minimizing errors between model and experimental marker trajectories. The approach is demonstrated by fitting a 27 parameter, three-dimensional, 12 degree-of-freedom lower-extremity kinematic model to synthetic and experimental movement data for isolated joint (hip, knee, and ankle) and gait (full leg) motions. For noiseless synthetic data, the approach successfully recovered the known joint parameters to within an arbitrarily tight tolerance. When noise was added to the synthetic data, root-mean-square (RMS) errors between known and recovered joint parameters were within 10.4° and 10 mm. For experimental data, RMS marker distance errors were reduced by up to 62% compared to methods that estimate joint parameters from anatomical landmarks. Optimized joint parameters found using a loaded full-leg gait motion differed significantly from those found using unloaded individual joint motions. In the future, this approach may facilitate the creation of dynamic patient-specific musculoskeletal models for predictive clinical applications.

Keywords: Multi-joint kinematics; Patient-specific models; Biomechanical optimization

1. Introduction

Dynamic patient-specific musculoskeletal models have great potential for addressing clinical problems in orthopedics and rehabilitation (Arnold et al., 2000; Chao et al., 1993; Delp et al., 1998; Pandy, 2001). Since dynamic models are built upon kinematic models, dynamic analyses and simulations are influenced by the associated kinematic model parameters such as joint axis positions and orientations (Andriacchi and Strickland, 1985; Challis and Kerwin, 1996; Davis, 1992; Holden and Stanhope, 2000; Stagni et al., 2000). Therefore, accurate patient-specific kinematic models are essential for creating predictive patient-specific dynamic models.

The literature contains three categories of methods to develop patient-specific kinematic models: anatomical landmark, functional, and optimization. The goal of each method is to determine the joint parameters that tailor the model to the patient. Anatomical landmark methods use percentages of distances between palpable bony landmarks to estimate joint parameters (Bell et al.,

*Corresponding author. Department of Mechanical & Aerospace Engineering, University of Florida, 231 MAE-A Building, P.O. Box 116250, Gainesville, FL 32611-6250, USA. Tel.: +1-352-392-8157; fax: +1-352-392-7303.

E-mail address: fregly@ufl.edu (B.J. Fregly).

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1990; Churchill et al., 1998; Inman, 1976; Kirkwood et al., 1999; Vaughan et al., 1992). However, they do not account for subject-to-subject anatomic variations. Functional methods fit a simple mathematical model, such as a sphere, to the motion of the distal segment with respect to the proximal segment (Leardini et al., 1999; Piazza et al., 2001). While this approach has clear application to the hip, it is less well defined for other joints. Optimization methods adjust joint parameters or model degrees of freedom to fit a kinematic model to experimental movement data. These methods have been developed for single-joint kinematic models with unknown joint parameters (Bogert et al., 1994; Sommer and Miller, 1980) and multi-joint models with fixed parameters (Lu and O'Connor, 1999) but not multi-joint models with unknown parameters.

This study presents a two-level optimization approach that simultaneously optimizes joint parameters and motion for multi-joint kinematic models. The approach works with any pre-defined multi-joint kinematic model for which experimental data are available from at least three markers per segment. Furthermore, the experimental data can come from a variety of sources, including video-based motion analysis with surface marker triads (Bogert et al., 1994; Leardini et al., 1999; Luchetti et al., 1998) or clusters (Andriacchi et al., 1998) and radiostereometric analysis (RSA) with implanted bone markers (Imai et al., 2003; Tashman and Anderst, 2003). The approach is demonstrated by fitting a 27 parameter, three-dimensional (3D), 12 degree-of-freedom (DOF) lower-extremity kinematic model to synthetic (i.e., computer generated) and experimental movement data for isolated joint and gait motions.

2. Materials and methods

Two-level optimization finds patient-specific joint parameters that best fit any pre-defined kinematic model to a patient's movement data (Sommer and Miller, 1980). An outer level optimization modifies the model's structure (defined by joint parameters p) and repeated inner level optimizations at each time frame modify the model's configuration (defined by generalized coordinates q) given the current model structure. The inner level optimization uses nonlinear least squares to minimize the sum of the squares of coordinate errors (x, y, and z) between model and experimental marker trajectories:

$$e_{\text{inner}}(\boldsymbol{p}) = \sum_{i=1}^{nf} \min_{q_i} \sum_{j=1}^{nm} \sum_{k=1}^{3} [m_{ijk} - m'_{jk}(\boldsymbol{p}, \boldsymbol{q}_i)]^2, \quad (1)$$

where nf is the number of time frames, q_i the model configuration at time frame i, nm the total number of markers ($nm \geqslant 6$), m an experimental marker, and m' the corresponding model marker (Lu and O'Connor, 1999). The outer level uses any desired optimization algorithm to modify joint parameters to minimize $e_{\text{inner}}(p)$ (Sommer and Miller, 1980; Bogert et al., 1994):

$$e_{\text{outer}} = \min_{\boldsymbol{p}} \; e_{\text{inner}}(\boldsymbol{p}). \quad (2)$$

Though the two-level optimization approach is applicable to any kinematic model, a 27 parameter, 3D, 12 DOF lower-extremity model was created as a sample application. The model was derived with symbolic manipulation software (Autolev™, Online Dynamics Inc., Sunnyvale, CA) and uses a 6 DOF joint to connect the pelvis to the ground, a gimbal (3 DOF) joint for the hip (Fig. 1), a pin (1 DOF) joint for the knee (Fig. 2), and two non-intersecting pin joints for the ankle (Fig. 3). Anatomical landmarks were used to estimate nominal values for the 6 hip (Bell et al., 1990), 9 knee (Churchill et al., 1998; Vaughan et al., 1992), and 12 ankle (Bogert et al., 1994; Inman, 1976) parameters.

Experimental movement data for testing the methodology were collected from one subject using reflective surface markers and video-based motion analysis (Motion Analysis Corporation, Santa Rosa, CA). Institutional review board approval and informed consent were obtained. The Cleveland Clinic marker set was used with additional markers placed on the foot segment. Static markers over the medial and lateral femoral condyles and medial and lateral malleoli were used in conjunction with dynamic markers to create segment coordinate

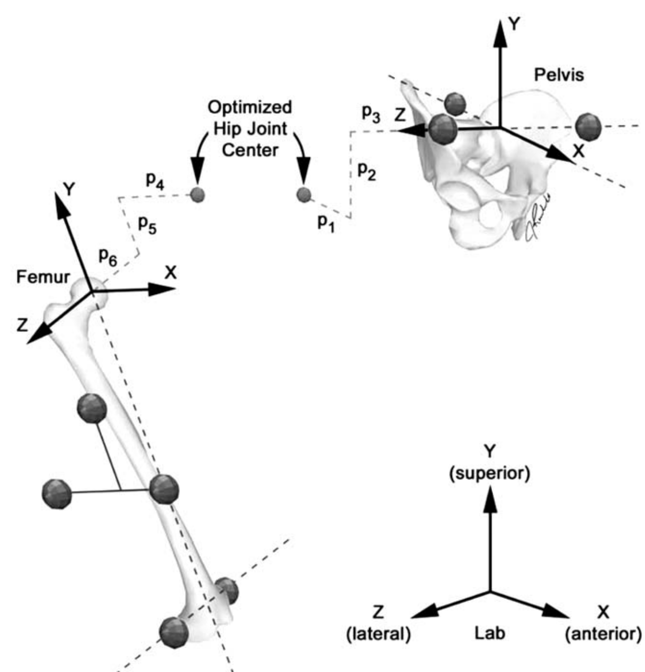

Fig. 1. Three DOF hip joint kinematic model and associated experimental surface markers. Six joint parameters p_1 through p_6 (all positions) are required to define the hip joint center in the pelvis and thigh coordinate systems.

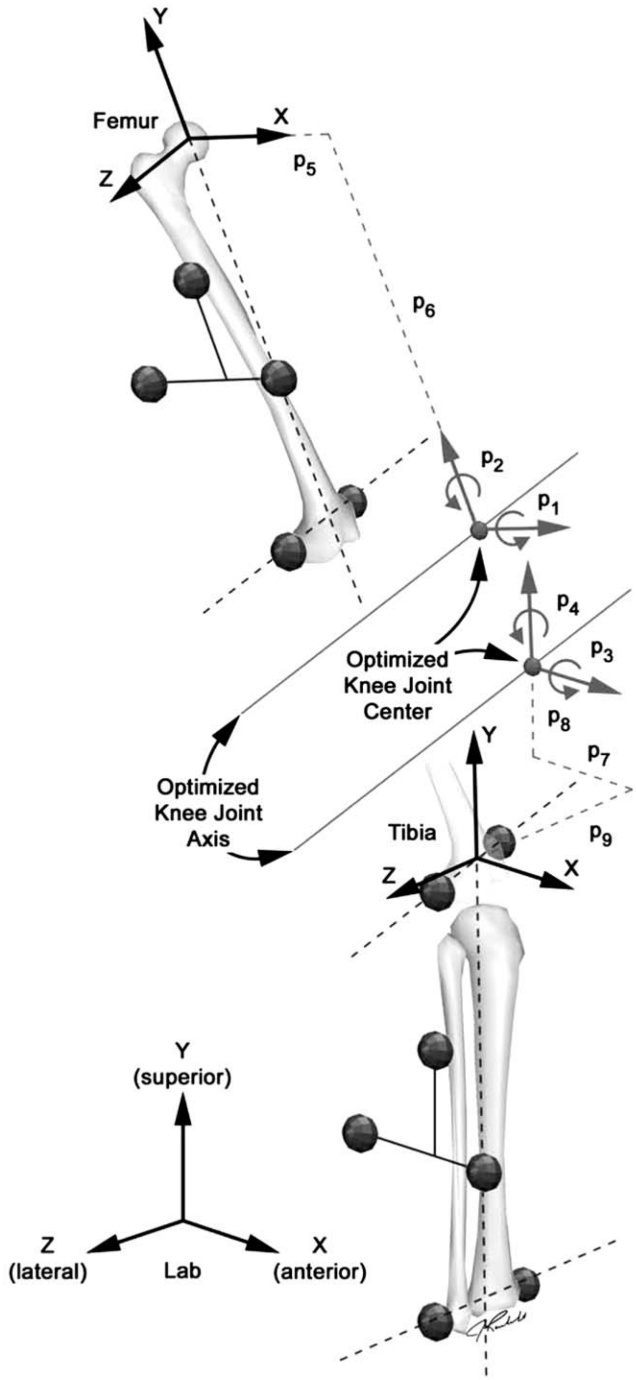

Fig. 2. One DOF knee joint kinematic model and associated experimental surface markers. Nine joint parameters p_1 through p_9 (four orientations and five positions) are required to define the knee joint axis in the thigh and shank coordinate systems.

systems (pelvis, thigh, shank, and foot). Only three dynamic markers per segment remained during experiments. Unloaded joint experiments (hip, knee, and ankle) were performed to exercise all functional axes of each joint individually. Gait data were collected to investigate simultaneous motion of all three joints under

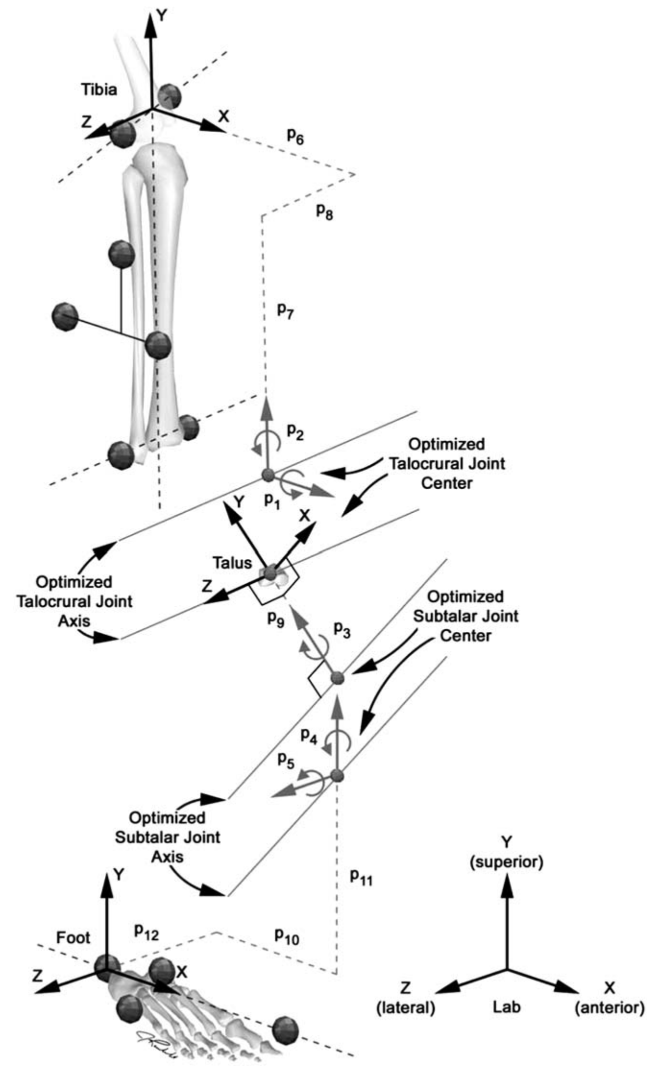

Fig. 3. Two DOF ankle joint kinematic model and associated experimental surface markers. Twelve joint parameters p_1 through p_{12} (five orientations and seven positions) are required to define the talocrural and subtalar joint axes in the shank and foot coordinate systems (Bogert et al., 1994).

load-bearing physiological conditions not exercising all functional axes. Raw marker data were filtered using a fourth-order, zero phase-shift, low pass Butterworth Filter with a cutoff frequency of 6 Hz (Bogert et al., 1994; Reinschmidt et al., 1997; Zeller et al., 2003).

Two types of synthetic movement data were generated from the experimental data to test the methodology further. The first type was noiseless synthetic data generated by moving the model through motions representative of the individual joint and gait experiments. The second type was synthetic data with superimposed numerical noise to simulate skin movement artifacts. A continuous noise model used in previous studies (Chéze et al., 1995; Lu and O'Connor, 1999; Roux et al., 2002) for similar purposes was employed. Noise parameters matched those of Chéze et al. (1995).

Table 1
Summary of root-mean-square (RMS) joint parameter and marker distance errors produced by two-level optimization and anatomic landmark methods for three types of movement data. Experimental data were from isolated joint and gait motions measured using a video-based motion analysis system with three surface markers per body segment. Synthetic marker data were generated by applying the experimental motions to a nominal kinematic model with and without superimposed numerical noise. The isolated joint motions were non-weight bearing and utilized larger joint excursions than did the gait motion. For the anatomical landmark method, only the inner level optimization was performed since the joint parameters were specified. The individual joint optimizations used isolated joint motion data while the full leg optimization used gait motion data

Movement data	Method	RMS error	Hip only	Knee only	Ankle only	Full leg
Synthetic without noise	Two-level optimization	Marker distances (mm)	3.89e-03	1.79e-02	3.58e-03	9.80e-05
		Orientation parameters (deg)	n/a	4.63e-02	1.85e-02	8.83e-02
		Position parameters (mm)	7.78e-05	9.49e-02	4.95e-03	6.05e-03
Synthetic with noise	Two-level optimization	Marker distances (mm)	5.20	4.23	5.68	5.65
		Orientation parameters (deg)	n/a	2.51	5.04	10.37
		Position parameters (mm)	1.66	3.46	10.04	8.16
Experimental	Two-level optimization	Marker distances (mm)	3.92	7.10	3.94	7.80
Experimental	Anatomical landmarks	Marker distances (mm)	5.47	14.23	10.29	13.66

The two-level optimization procedure was applied to all three data sets (synthetic data without noise, synthetic data with noise, and experimental data). For individual joint trials, parameters for each joint were optimized separately. For comparison, parameters for all three joints were optimized simultaneously for the gait trial. To demonstrate the procedure's versatility, a particle swarm global optimizer (PSO) (Kennedy and Eberhart, 1995) was used for single-joint optimizations while a gradient-based local optimizer (VisualDOC, Vanderplaats R&D, Colorado Springs, CO) was used for multi-joint optimization. Both algorithms were implemented in a cluster-computing environment. Root-mean-square (RMS) errors in recovered joint parameters (synthetic data only) and marker distances were used to quantify the procedure's performance.

3. Results

The two-level optimization procedure successfully recovered joint parameters that best matched the synthetic and experimental movement data. For synthetic motions without noise, the two-level optimizations recovered the original marker trajectories to within an arbitrarily tight tolerance (Table 1—first data set). The original joint parameters for the hip, knee, and ankle were recovered with RMS orientation errors of less than 0.09° and RMS position errors less than 0.1 mm. For synthetic motions with noise, RMS errors in recovered joint positions (within 10 mm) and orientations (within 10.4°) increased with joint complexity (Table 1—second data set) while RMS marker distance errors (about 5 mm) were comparable to the amplitude of the synthetic noise ($\leqslant 10$ mm). For experimental motions, the optimizations reduced RMS marker distance errors by 28% for the hip, 50% for the knee, 62% for the ankle, and 43% for the full leg compared to errors found using anatomical landmark methods, with the maximum RMS distance error being 7.8 mm (Table 1—third and fourth data sets). For the individual joint motions, the RMS difference between optimized and anatomical landmark parameters was about 7° for joint orientations and 15 mm for joint positions, while for the full leg gait motion, they were 14° and 23 mm (Table 2).

4. Discussion

This study has presented a two-level optimization approach for tuning a multi-joint kinematic model to experimental movement data from a specific patient. The approach works with any pre-defined kinematic model structure and any experimental movement data for which at least three markers per segment are measured. As demonstrated with a 27 parameter, 3D, 12 DOF lower extremity model, two-level optimization is able to reduce RMS marker distance errors by roughly a factor of two compared to anatomical landmark methods.

As with any optimization problem, the issue of local versus global optima is present for the two-level formulation. Inner level optimizations are extremely robust to poor initial guesses, and seeding the subsequent time frame with joint angles from the previous time frame is sufficient to ensure convergence. In contrast, outer level optimizations are less robust if the gradient-based algorithm is used. For example, when the ankle joint optimization was solved with the gradient-based algorithm using synthetic data with noise and 10 physically realistic initial guesses, it rarely converged to the PSO solution (Schutte et al., 2003), indicating the presence of local minima. Convergence was improved by scaling joint parameters to be within $[-1,1]$. Thus, the full-leg optimization used scaling and was seeded with joint parameters found by the PSO algorithm from individual joint optimizations.

Table 2
Comparison between joint parameters predicted by anatomical landmark methods, two-level optimization of individual joints separately, and two-level optimization of all joints simultaneously. Body segment indicates the segment in which the associated joint parameter is fixed. For a graphical depiction of the listed joint parameters, consult Figs. 1–3

Joint	Joint parameter (mm or deg)	Body segment	Anatomical landmarks	Single joint optimizations	Full leg optimization
Hip	Anterior position	Pelvis	−59.31	−75.19	−67.81
	Superior position	Pelvis	−91.67	−92.69	−84.13
	Lateral position	Pelvis	86.28	88.58	134.64
	Anterior position	Thigh	0.00	−21.23	8.88
	Superior position	Thigh	0.00	8.14	13.12
	Lateral position	Thigh	0.00	14.38	67.08
	Frontal plane orientation	Thigh	0.00	−0.59	17.40
	Transverse plane orientation	Thigh	0.00	14.85	12.19
Knee	Frontal plane orientation	Shank	−4.07	−2.72	6.19
	Transverse plane orientation	Shank	1.54	2.40	13.89
	Anterior position	Thigh	0.00	−14.22	−22.17
	Superior position	Thigh	−392.11	−396.12	−390.54
	Anterior position	Shank	0.00	−2.50	−14.79
	Superior position	Shank	0.00	−4.57	−4.99
	Lateral position	Shank	0.00	14.72	14.10
Ankle (Talocrucal)	Frontal plane orientation	Shank	8.81	16.64	−5.07
	Transverse plane orientation	Shank	0.00	9.54	10.37
	Anterior position	Shank	0.00	16.51	23.56
	Superior position	Shank	−411.32	−411.86	−418.79
	Lateral position	Shank	0.00	−15.10	−16.33
Ankle (Subtalar)	Transverse plane orientation	Talus	26.89	27.36	10.24
	Transverse plane orientation	Foot	23.00	13.20	14.74
	Sagittal plane orientation	Foot	42.00	45.26	37.39
	Superior position	Talus	−12.40	−21.42	−9.49
	Anterior position	Foot	91.14	112.44	115.80
	Superior position	Foot	39.01	38.51	29.38
	Lateral position	Foot	11.17	2.83	−14.31

There are two likely explanations for why joint parameters found by the full-leg optimization differed greatly from those found by individual joint optimizations using experimental data. First, loading conditions were different in these two scenarios. It is possible that best-fit joint parameters vary as a function of joint loading (Bogert et al., 1994). Furthermore, loading may affect which pre-defined joint model is most appropriate. In the knee, for example, internal/external rotation near full extension indicates that a 2 DOF knee joint may be more appropriate for gait, depending on the intended use of the model. Second, the amount of joint excursion was different in each scenario. Individual joint trials exercised all functional axes of every joint, whereas the gait trial did not exercise some functional axes significantly (e.g., hip abduction/adduction). As a result, noise in the gait data made the cost function insensitive to large changes in poorly exercised joint parameters. An important research area for future studies will be the development of a systematic methodology for determining which joint parameters can and cannot be found accurately from a particular noisy experimental data set.

An important limitation of the two-level optimization approach is that the quality of the recovered joint parameters will only be as good as the quality of the available experimental movement data. This is demonstrated clearly in the synthetic data with noise optimizations, where recovered joint parameters did not match original ones but still resulted in a lower cost function value. Thus, we can only claim that optimized joint parameters provide the best possible fit to imperfect experimental movement data. However, this fit was still significantly better compared to anatomical landmark methods.

In conclusion, the proposed two-level optimization approach is able to tune a pre-defined multi-joint kinematic model to match a patient's experimental movement data as closely as possible. With current computing power, the approach requires parallel processing to complete in a reasonable amount of time. Local optimization requires less time than global optimization but does not provide the same level of confidence in the solution given local minima caused by measurement noise. Patient-specific kinematic models created with this approach may facilitate development of dynamic musculoskeletal models for predicting functional outcome following surgical and rehabilitation interventions.

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