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Improving joint torque calculations: Optimization-based inverse dynamics to reduce the effect of motion errors

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Abstract

The accuracy of joint torques calculated from inverse dynamics methods is strongly dependent upon errors in body segment motion profiles, which arise from two sources of noise: the motion capture system and movement artifacts of skin-mounted markers. The current study presents a method to increase the accuracy of estimated joint torques through the optimization of the angular position data used to describe these segment motions. To compute these angular data, we formulated a constrained nonlinear optimization problem with a cost function that minimizes the difference between the known ground reaction forces (GRFs) and the GRF calculated via a top-down inverse dynamics solution. To evaluate this approach, we constructed idealized error-free reference movements (of squatting and lifting) that produced a set of known "true" motions and associated true joint torques and GRF. To simulate real-world inaccuracies in motion data, these true motions were perturbed by artificial noise. We then applied our approach to these noise-induced data to determine optimized motions and related joint torques. To evaluate the efficacy of the optimization approach compared to traditional (bottom-up or top-down) inverse dynamics approaches, we computed the root mean square error (RMSE) values of joint torques derived from each approach relative to the expected true joint torques. Compared to traditional approaches, the optimization approach reduced the RMSE by 54% to 79%. Average reduction due to our method was 65%; previous methods only achieved an overall reduction of 30%. These results suggest that significant improvement in the accuracy of joint torque calculations can be achieved using this approach.

Keywords: Inverse dynamics; Optimization; Joint moments; Error reduction

1. Introduction

Inverse dynamics is a method commonly used in the biomechanical analysis of human movement to calculate the net torque (or muscle moment) due to the contraction of muscles spanning each joint. This method uses kinematic, kinetic, and anthropometric information as input to solve the Newton–Euler equations of motion for each body segment (Winter, 2005).

Despite the widespread use of the inverse dynamics method, researchers recognize that it is error prone. The literature suggests that the main sources of error are: (1) inaccuracy in movement coordinate data, (2) estimations of body segment parameters, (3) errors related to force plate measurements, and (4) identification of joint center of rotation locations (e.g., Bell et al., 1990; Kuo, 1998; Schwartz and Rozumalski, 2005; Riemer et al., in press). Inaccuracy in movement coordinate data affects the calculation of the motions of individual body segments (i.e., segment angles and accelerations). This inaccuracy is caused by two types of errors: (a) error in marker location due to inherent motion capture system noise (Richards, 1999) and (b) relative motion between skin-mounted markers and the underlying bone (a.k.a. skin movement artifact) (Cappozzo et al., 1996; Fuller et al., 1997; Holden et al., 1997). We have found that these various inaccuracies can result in uncertainties of estimated joint torques ranging from 6% to 232% of the peak torque (Riemer et al., in press).

Two approaches have traditionally been used for inverse dynamics computations. The first requires only kinematic

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and anthropometric data to calculate joint torques. This process, often referred to as the top-down approach, typically starts at the (unloaded) distal segment of the upper extremity(ies) and proceeds downward such that dynamic equilibrium conditions are satisfied for each successive segment. The top-down approach, however, is quite sensitive to the propagation of inaccuracies, including those affecting acceleration data (Cahouet et al., 2002); thus, this method is not typically used to compute both proximal and distal (e.g., upper and lower extremity) joint torques simultaneously. The second method tends to improve torque estimates for the lower extremity and reduce acceleration effects by adding kinetic data, typically ground reaction forces (GRFs) for locomotor tasks. This method, often called the bottom-up approach, starts at the distal segment of one or both lower extremities and proceeds upward through the body. By incorporating GRF measurements, boundary conditions are defined for the bottommost segment. These added conditions result in redundant information since there are now more equilibrium equations than system unknowns. Some research groups have suggested that these conditions result in an over-determined system (Vaughan et al., 1982; Kuo, 1998; Cahouet et al., 2002). As a consequence, due to errors such as those mentioned above, these traditional methods can result in residual forces and torques on the most-distal segment.

This redundancy has been used to reduce error effects through optimization methods, which based their cost function upon minimizing these residuals. These optimization methods adjust specific input parameters in the top-down calculations until optimal values are found that minimize the difference between the known ground reaction measurements and those predicted through the top-down calculation.

These optimization methods have been used to (i) determine an optimal set of body segment parameters (Vaughan et al., 1982), (ii) reduce the effect of noise in measured data (i.e., GRF measurements and segment motion) (Kuo, 1998), and (iii) calculate optimal segment accelerations in order to improve joint torque calculations (Cahouet et al., 2002). Vaughan et al. (1982) and Cahouet et al. (2002) assumed that minimizing a cost function is sufficient for improving results; however, their cost functions did not contain information on the joint torques, and therefore it is possible to minimize their cost functions but also increase error in the joint torques. Kuo (1998) overcame this situation by suggesting an additional success criterion, which stated that the difference between the optimized and simulation-based reference or "true" joint torque value should be less than the traditional (non-optimized) inverse dynamics solution. Cappozzo (2002) and Mazza and Cappozzo (2004) recently proposed a method that used GRF data to compute optimal solutions for joint angular motion. Their motivation was to find a technique that used only GRF data to estimate joint motion.

These studies, though, were not designed to eliminate the effect of characteristic error in the motion profiles. Previously, it was found that inaccuracy in estimated segment angular position (and associated acceleration) is the main contributor to uncertainty in joint torque solutions (Leardini et al., 2005; Riemer et al., in press). Therefore, an optimization method that could reduce errors in movement data and account for both motion capture system noise and skin movement artifact should provide the greatest improvement. This paper extends these past studies by describing an optimization problem to find optimal angular position data to reduce error in estimated joint torques.

2. Method

The goal of this work was to develop a method to increase the accuracy of estimated joint torques through the optimization of angular position data used to describe body segment motions. Specifically, we formulated a constrained nonlinear optimization problem with a cost function that minimized the difference between the known GRFs and the GRF calculated via a top-down inverse dynamics approach. We evaluated the efficacy of this approach by examining simple planar reference motions of three- or four-segment systems (Fig. 1). More specifically, we constructed two reference motions (squatting with arms crossed and lifting with straight arms) that generated a set of error-free test data. We refer to these data as the true segment angle profiles, joint coordinates, joint torques, and GRF. Artificial noise was then added to the true motion data to mimic real-world data. These noisy data were then used to compute joint torques via our optimization approach and traditional (bottom-up and top-down) approaches. Relative to the true values, results from optimized segment angle profiles and related joint torques were then compared to results derived from the traditional non-optimized approaches.

2.1. Optimization formulation

The general formulation for the optimization problem was

$$\begin{aligned} \min \quad & z(v) \\ \text{s.t.} \quad & \begin{cases} c_k(v) = 0, & k \in E, \\ c_k(v) \geqslant 0, & k \in I, \end{cases} \end{aligned} \tag{1}$$

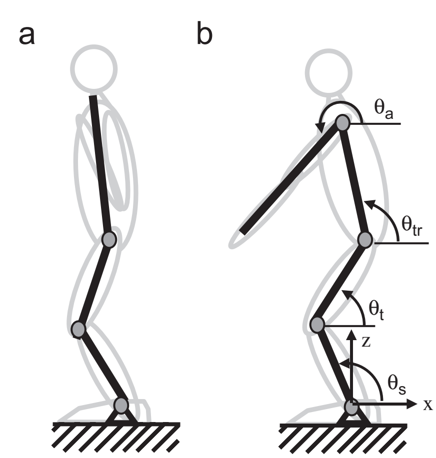

Fig. 1. Squatting (a) and lifting (b) motions were represented by three- and four-segment models, respectively. Segment angles for the shank (θ_s), thigh (θ_t), torso (θ_{tr}), and arm (θ_a) were defined as shown.

where z is the objective function, $c_k(v) = 0$, $k \in E$ are equality constraints, $c_k(v) \geqslant 0$, $k \in I$ are inequality constraints, and v is a vector of optimization variables (i.e., segment angles). The objective function was the least square of the difference between the calculated forces obtained with a top-down approach and the known GRF. The 2D objective function therefore was:

$$z = \sum_{i=1}^{n} [(f_i^x(v) - \bar{f}_i^x)^2 + (f_i^z(v) - \bar{f}_i^z)^2 + (\tau_i^y(v) - \bar{\tau}_i^y)^2], \tag{2}$$

where i is the time index and n is total number of time intervals during the chosen motion. f^x, f^z, τ^y are the calculated GRFs and torque (using a top-down approach) as a function of the optimization variables v. $\bar{f}^x, \bar{f}^z, \bar{\tau}^y$ are the known ground reactions (i.e., "true" values when considering an idealized perfect system, or "measured" values when considering a real-world experimental system). Directions x, y, z are defined in Fig. 1.

The equations of motion used to calculate the joint torques and GRFs and moments were subject to kinematic constraints that related the segment angles to the position of each segment's center of mass. The following equations are examples of constraints for the center of mass location (x, z) of segment 2 as a function of the segment angles:

$$\begin{cases} x_{i,2} = L_1 \cos(\theta_{i,1}) + d_2 \cos(\theta_{i,2}), \\ z_{i,2} = L_1 \sin(\theta_{i,1}) + d_2 \sin(\theta_{i,2}), \end{cases} \tag{3}$$

where L_1 is the length of segment 1 (i.e., the shank), d_2 is the distance from the proximal end of segment 1 to the center of mass location of segment 2, and θ is the respective segment angle. For a detailed description of this formulation refer to Kuo (1998).

The objective function was minimized under the following constraints on the motion parameters. Equality constraints (E) were used to calculated angular velocity and acceleration of each segment. These values were obtained using the central finite difference method. Inequality constraints (I) were based on the literature and previous knowledge of the system to give a range in which the solution could be found. Angular positions were limited to upper and lower bounds:

$$\bar{\theta}_{i,j} + \varepsilon_a \geqslant \theta_{i,j} \geqslant \bar{\theta}_{i,j} - \varepsilon_a, \tag{4}$$

where $\bar{\theta}_{i,j}$ is the known angle, $\theta_{i,j}$ is the optimized value, and j is segment index. ε_a is the maximum possible error in the known angle and can be derived from skin movement artifact studies (Cappozzo et al., 1996; Holden et al., 1997; Stagni et al., 2005). Another inequality constraint was based on the kinematic configuration, such that error in the location of each joint center, as measured by the motion capture system compared to the location predicted by the optimization (i.e., function of segment angle and link length), had to fall within a specified range ε_m. In 2D, these constraints take the following form:

$$\varepsilon_m \geqslant \left[\bar{x}_{i,m} - \sum_{j=1}^{m} L_j \cos(\theta_{i,j})\right]^2 + \left[\bar{z}_{i,m} - \sum_{j=1}^{m} L_j \sin(\theta_{i,j})\right]^2, \tag{5}$$

where m is joint number and $\bar{x}, \bar{z}$ are known joint center coordinates. ε_m can be derived from joint center studies (Bell et al., 1990; Leardini et al., 1999; Roux et al., 2002; Schwartz and Rozumalski, 2005).

In summary, using the proposed optimization algorithm, the vector of optimization variables (i.e., segment angles) was manipulated in order to minimize the least square of the difference between the calculated and known GRF (Eq. (2)). Optimized angular profiles and optimization-based joint torques were the final output from this procedure (Fig. 2). Our formulation was solved using SNOPT (large-scale SQP-based NLP solver from Stanford University) and executed using the General Algebraic Modeling System (GAMS, Washington, DC), which is a high-level modeling and optimization package.

2.2. Assessment of the optimization methodology

2.2.1. True test data construction

We evaluated the performance of our method by first constructing idealized, error-free systems to use as test data. These multi-body systems consisted of either a three- or four-segment body that performed simple sagittal-plane reference motions, i.e., squatting or lifting, respectively (Fig. 1). From these motion data, it was possible to create sets of "true" (noise-free) reference segment angle profiles, movement coordinate data, GRFs, and joint torques. Our squatting motion mimicked a person lowering into a squat and then standing up with arms across the chest; the three segments were the shanks, thighs, and torso (including head and arms). The lifting motion involved the basic squatting motion with the addition of a fourth segment representing straightened arms that mimicked picking up a package from the floor. Segment angles for the shanks, thighs, torso (including head), and arms (θ_s, θ_t, θ_{tr}, θ_a) defined the orientation of each segment. Since the feet were assumed to be stationary with respect to ground, the ankle joint was pinned directly to the ground, and the GRFs and torques were reduced to this stationary ankle joint (Mazza and Cappozzo, 2004).

To generate the desired motion data, we used established techniques to construct reference motion profiles from captured kinematic data (e.g., Cheze et al., 1995; Lu and O'Connor, 1999; Roux et al., 2002; Mazza and Cappozzo, 2004; Reinbolt et al., 2005). Specifically, segment angle profiles of squatting and lifting were derived from kinematic data of a single individual collected with a motion capture system (model 460; Vicon Motion Systems; Oxford, UK; sampled at 50 fps). Analytical expressions

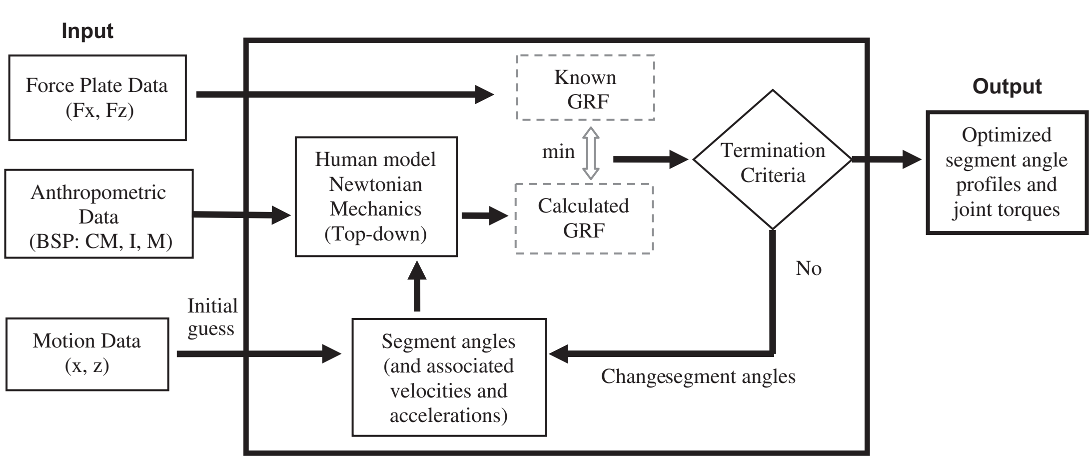

Fig. 2. The algorithm manipulates the optimization variables (segment angles) to minimize the difference between known and calculated ground reaction forces. The process outputs are the optimized segment angles and joint torques.

for these reference motions were then created by fitting the angular profiles to a 15th-order polynomial function (*polyfit* function; MATLAB; The MathWorks, Inc.; Natick, MA, version 6.5). These baseline analytical profiles were considered to be the "true" segment angular profiles. True 2D joint center coordinate data (x, z) were then generated from these analytical profiles.

Using the true motion data, reaction forces and torque at each joint were determined by using the top-down inverse dynamics approach. The reaction forces and torque at the ankle joint were considered to represent the true GRFs and torque (i.e., "true GRF" or $\bar{f}^x, \bar{f}^z, \bar{\tau}^y$ in Eq. (2)). Likewise, the torque values at the ankle, knee, hip, and shoulder were considered to be their true joint torques. Since the top-down approach also required anthropometric data, body segment parameters (i.e., segment mass, moment of inertia, center of mass location, and link length) were derived for a body with height 1.8 m and mass 80 kg (Chaffin et al., 1999).

2.2.2. *Noisy experimental data construction*

Next, to simulate real world conditions that affect motion measurement, error in the coordinate data (x, z) was introduced by adding artificial noise to mimic noise from the motion capture system and skin movement artifacts. Error due to skin movement artifact was simulated by a sinusoidal noise model derived from prior models in the literature (e.g., Cheze et al., 1995; Lu and O'Connor, 1999; Roux et al., 2002; Reinbolt et al., 2005; Schwartz and Rozumalski, 2005). The model parameters were set to cause segment angular error to be similar to measurements error as they were reported in the literature (e.g., (Cappozzo et al., 1996; Holden et al., 1997; Stagni et al., 2005). Noise in the motion capture system was simulated using zero-mean white noise with a standard deviation of 0.60 mm (Richards, 1999). Noise model parameters were varied such that 10 non-specific, noise-induced, coordinate data sets were created for each motion; these data sets are comparable to experimental data collected from 10 trials per motion. The noise-induced coordinate data were then low-pass filtered using a second-order forward-backward Butterworth filter, with 5 Hz cut-off frequency (Winter, 2005). These coordinate data were converted into segment angular profiles (Winter, 2005), and used as the initial guess for the optimization. Recall that the vector of optimization variables v consists of the segment angles. (In a real-world experimental setting, the initial guess of the angular profiles would be based on the measured profiles.)

2.3. *Data analysis*

To examine the effect of our optimization-based inverse dynamics approach on joint torque estimations, 10 "trials" per motion were generated from the noisy data. For each trial, the average root mean square error (RMSE) between the true and optimization-based torque was computed for each joint. RMSE values were also computed between true joint torques and values obtained when the noisy data were used in non-optimized (traditional) inverse dynamics solutions using both bottom-up and top-down approaches. Segment angle RMSE and maximum error (MAXerror) between the true value and the optimized or initial noise-induced value were also calculated. In addition, percent improvements of the optimized solutions relative to the smallest RMSE (or MAXerror) achieved using either traditional approach were calculated for each joint.

The original optimization algorithm proposed by Cappozzo (2002) and Mazza and Cappozzo (2004) required knowledge of the initial and final positions for the joint angle profiles. Our formulation, however, set no constraints* on these boundary conditions, since in reality they are rarely known. (*With the exception of optimization constraints in Section 2.1.) As a result we expected the error in the optimized angles and torques to be larger near the beginning and end of the optimization time window. To assess this boundary effect, all parameters (e.g., RMSE, MAXerror) were calculated first for the full set of data (*FullSet*) and then when the beginning and last 0.2 s were excluded (*Truncated*).

Table 1
Average RMSE and maximum error (compared to true value) for segment angles over 10 trials during simulated squatting or lifting motions using initial noise-induced data and the optimized solution

	Squat (deg)		Lifting (deg)	
	Full set[a]	Truncated[a]	Full set	Truncated
RMSE				
θ_s Shank				
Initial	1.61	1.57	1.77	1.83
Optimized	0.92	0.69	1.03	0.90
θ_t Thigh				
Initial	2.74	2.47	2.73	2.24
Optimized	1.03	0.35	1.23	0.52
θ_{tr} Torso				
Initial	2.27	2.07	2.66	2.59
Optimized	1.33	0.83	1.19	1.03
θ_a Arm				
Initial	–	–	1.83	1.93
Optimized	–	–	1.34	1.24
MAXerror				
θ_s Shank				
Initial	2.86	2.44	3.28	3.14
Optimized	2.17	1.08	2.28	1.49
θ_t Thigh				
Initial	5.15	4.49	5.73	4.84
Optimized	3.10	0.77	4.16	1.20
θ_{tr} Torso				
Initial	4.58	3.75	4.71	4.61
Optimized	3.40	1.47	2.88	1.55
θ_a Arm				
Initial	–	–	3.10	3.04
Optimized	–	–	2.53	2.13

[a]Boundary effects: includes (full set) or excludes (truncated) beginning and ending 0.2 s of data.

3. Results

The optimization algorithm successfully converged for all trials, and always reduced the difference between the true and calculated GRF to values less than 0.001 N or 0.001 N m for ankle torque (RMSE). For both motions, this approach always improved the replication of true segment angle behavior compared to the initial noisy data (27% to 62% improvement in RMSE and 18% to 40% in MAXerror; *FullSet* results; Table 1, Fig. 3). Consequently, the optimization approach outperformed traditional inverse dynamics approaches by estimating more accurate knee, hip, and shoulder torques during both motions (54% to 66% improvement in RMSE—*FullSet*; Table 2, Fig. 5).

Since no boundary condition constraints were specified, the joint torque and angular profiles tended to have larger errors at the beginning and end of the motion, i.e., first and last ~0.2 s (Figs. 3 and 4). Similar results were noted for squatting and lifting motions. Therefore, compared to *FullSet* results, RMSE, and MAXerror values computed using *Truncated* data always resulted in greater improvements for the optimized values (segment angles: 51% to

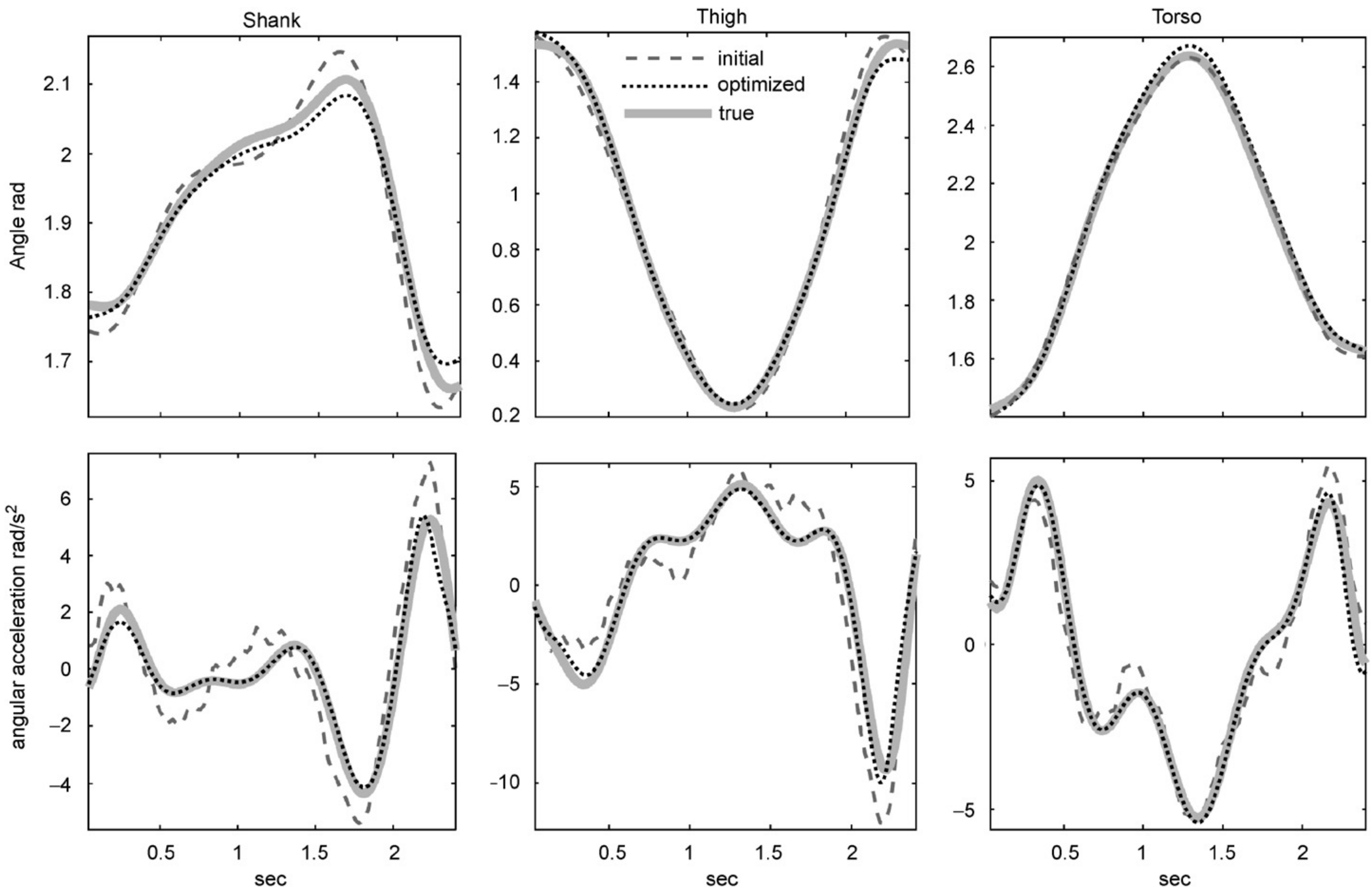

Fig. 3. Typical segment angular position and acceleration profiles during the squatting motion illustrating results for the true noise-free, initial noise-induced, and the final optimized motion profiles. Similar levels of improvement were found for the lifting motion.

Table 2
Average joint torque RMSE between true torque and optimized or traditional (top-down, bottom-up) methods over 10 trials during simulated squatting and lifting motions

	Squat (N m)		Lifting (N m)	
	Full set[a]	Truncated[a]	Full set	Truncated
Optimized				
Ankle	0.00	0.00	0.00	0.00
Knee	4.51	3.62	5.14	4.51
Hip	5.04	3.22	4.49	4.18
Shoulder	–	–	0.45	0.42
Top-down				
Ankle	47.65	43.30	39.37	41.49
Knee	30.29	24.38	21.33	20.03
Hip	25.94	27.51	24.36	25.95
Shoulder	–	–	1.14	1.00
Bottom-up				
Ankle	0.00	0.00	0.00	0.00
Knee	9.90	10.58	11.39	12.20
Hip	13.78	15.32	13.00	10.14
Shoulder	–	–	9.82	9.83

[a]Boundary effects: includes (full set) or excludes (truncated) beginning and ending 0.2 s of data.

86% improvement in RMSE and 30% to 83% in MAXerror; joint torques: 58% to 79% RMSE; Tables 1 and 2).

4. Discussion

This study utilized the redundant nature of the inverse dynamics method to reduce errors in joint torque estimations by formulating an optimization problem to find optimal segment angular profiles (Fig. 2). By using constructed error-free test data, we were able to evaluate the effectiveness of this approach compared to traditional non-optimized inverse dynamics methods relative to an idealized true benchmark.

The proposed approach resulted in joint torque and segment angle estimations that were equivalent or better than previous methods. By reducing errors in segment angular profiles, the optimization approach resulted in improvements of 54–79% in joint torque estimations (Table 2). It is important to mention that, due to the optimization procedure, the error in ankle torque is practically zero. This result, along with improvements in torque estimations across all joints, is an improvement

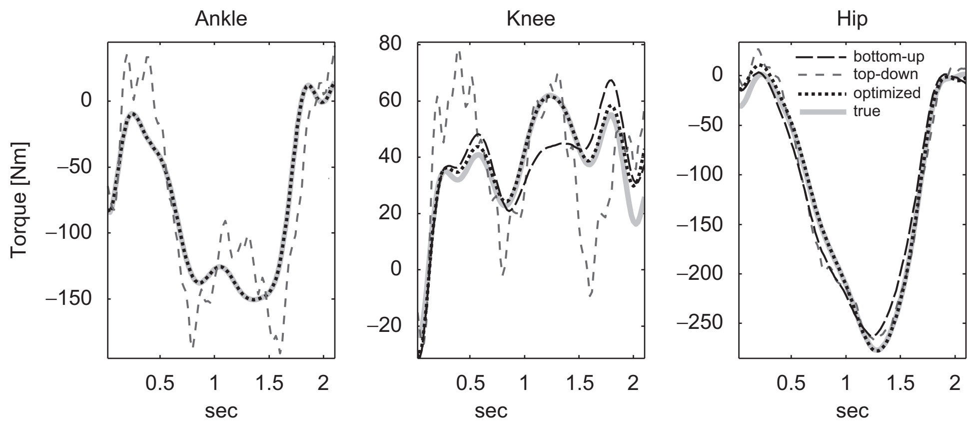

Fig. 4. Typical joint torque estimations during the squatting motion illustrating results for true noise-free, traditional (bottom-up or top-down), and optimization-based inverse dynamics methods. Similar results were found for the lifting motion.

when compared to Kuo (1998), who improved hip (by 45%) and overall torque estimation (30%) at the expense of ankle and knee torques. The reduction in segment angle errors ranged from 27% to 86% (RMSE), which are similar to results from methods that reduce skin movement artifacts, such as marker clusters (Alexander and Andriacchi, 2001) or joint constraints (Cheze et al., 1995; Lu and O'Connor, 1999; Reinbolt et al., 2005). Since our method and these methods are based on different principles, it is possible that by combining our approach with such methods, additional error reductions could be achieved.

Our optimization method built upon an approach proposed by Cappozzo (2002) and Mazza and Cappozzo (2004), which used a GRF-based optimization approach to estimate joint kinematics. A key difference in our formulation is that we eliminated the need to know and apply boundary conditions on the angle profiles, which in reality are rarely known. While we found that segment angle and torque estimations were always better after optimization whether the full or truncated data set were used, the truncated results were slightly better since slightly larger deviations from true values occurred at the beginning and end of the motion (Figs. 3 and 4, Tables 1 and 2). These results suggest that, if one were interested in examining the best possible results, it would be best to disregard the angle and torque data for a small portion of the beginning and end of a sampled motion when using this optimization-based method. For example if possible, one could sample the motion for a longer time period and then truncate the data to the period of interest.

To demonstrate the applicability of our optimization-based inverse dynamics approach to real experimental data, we performed an experiment with a single male test subject (height 1.9 m, mass 74.3 kg) wearing shoes (mass of 0.8 kg) (Riemer, 2007). The subject performed four sagittal plane motions at natural speed: torso leaning, sway about the hips, and two different squatting motions (Squat 1, Squat 2). During all motions, the subject held his arms across the chest, did not move his feet during the motion, and was told to keep his back as straight as possible in order to better represent the torso as a single rigid link segment. In torso leaning, the test subject flexed the torso forward to approximately 45° and then returned to an erect posture. Motion and GRF data were collected (model 460, Vicon Motion Systems, Oxford, UK and model BP600900, AMTI, Watertown, MA, respectively, both sampled at 100 Hz). A foot segment was also included in this model. Since true values were not available for experimental data, the difference between the estimations for angular profiles and joint torque obtained using our optimization approach and traditional (bottom-up and top-down) approaches were calculated.

This exercise demonstrated that, as desired, optimized segment angles varied little from the original motion profiles, while considerable differences (similar to the simulated study) were found between joint torques derived from our optimization method and traditional methods. Over the four motions, segment angle RMSE for the shank ranged from 1.2° to 2.3°, 1.7° to 3.4° for the thigh, and 2.3° to 3.4° for the HAT. Comparison between joint torques as calculated using the optimization method to the top-down approach resulted in RMSE for the ankle that ranged from 19.1 to 39.1 N m, 12.4 to 27.7 N m for the knee, and 4.9 to 9.0 N m for the hip. Comparison of optimization to bottom-up method results found RMSE for the ankle that ranged from 2.8 to 5.5 N m, 10.1 to 15.4 N m for the knee, and 10.6 to 25.4 N m for the hip.

This study is subject to limitations. First, in accordance with traditional inverse dynamics studies, body segments were assumed to be rigid links. Researchers have concluded that during high-impact motions, a non-rigid wobbling mass model may be more suitable (Gruber et al., 1987). This assumption therefore limited our analysis to relatively slow motions with low impact. Second, our method may not be able to correct for motions of small body parts (e.g., fingers), since these have relatively small effects on the ground reaction. Third, we did not consider the effects of inaccuracies of two other key input variables in joint torque estimations (GRF measurements and body segment parameters, Fig. 2). Finally, this study used a 2D model with three or four degrees of freedom (DOF) to represent the human musculoskeletal system. To better represent the human body and to accommodate analyses of more complicated motions, such as asymmetric motions, 2D or 3D models with greater DOF are necessary. Future studies on the development of this method to a fully applicable method should extend the proposed approach to accommodate these limitations and evaluate the method using methods such as fluoroscopy (Stagni et al., 2005) or by testing individuals with artificial limbs where it may be possible to instrument the joint to obtain the true joint torque.

Despite these limitations, this study demonstrates the potential of the optimization-based inverse dynamics approach. This approach significantly reduces errors in inverse dynamics solutions of joint torques by optimizing segment motion profiles when errors in motion measurements were present.

Conflict of interest statement

None of the authors has a potential conflict of interest (e.g., consultancies, stock ownership, equity interests, patent-licensing arrangements) related to the manuscript or the work it describes.

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