ABSTRACT

Background: Experimental and modeling errors can lead to dynamically inconsistent results when performing inverse dynamic analyses of human movement. Adding low-value residual pelvis actuators could deal with such a problem. However, in certain tasks, these residuals may remain quite large, and strategies based on motion or force variation must be applied.

Research question: Can the dynamic inconsistency be handled by an optimal control algorithm that changes the measured kinematics in the preparatory phase of the single leg triple hop test, a relatively high-speed and torque-demanding task, so that residuals are kept within a low range?

Methods: The proposed optimal control algorithm was developed as a tracking problem, in which the implicit form of dynamics was used. Equations of motion were introduced as path constraints, as well as residual forces and moments acting on the pelvis. To do so, GPOPS-II and IPOPT were employed to solve the optimization problem. Furthermore, OpenSim API was called at each iteration to solve the equations of motion through an inverse dynamic analysis.

Results: Results presented a high reduction in all six components of residual actuators during the entire task. Moreover, resulting motion after the optimization showed a very similar evolution than the reference motion before the ascending phase of the task. Once the ascending phase started, some coordinates presented a more significant discrepancy compared to the reference, such as the pelvis tilt and lumbar extension.

Significance: The findings suggest that the proposed algorithm can deal with dynamic inconsistency in high-speed tasks, obtaining low residual forces and moments while keeping similar kinematics. Hence, it could complement other optimal control algorithms that simulate new motions, relying on dynamically consistent data.

KEYWORDS

Biomechanics; Residual reduction; Optimal control; Triple hop test; Inverse dynamics.

INTRODUCTION

Optimal control simulation of human movement allows analyzing and assessing the biomechanics of specific tasks. Based on measurements of kinematics and contact forces, the balance between external and inertial forces and moments becomes inconsistent due to several sources of experimental and modeling errors [1]. Strategies to cope with such dynamic inconsistency are based on adding low-value residual force and torque actuators to the pelvis segment [2]. However, in high-speed tasks these residual actuators values usually remain large [3], which might invalidate the conclusions of the dynamic analysis.

In such those cases, procedures based on modifying force and motion data are employed. One way is to maintain kinematics and modify experimental external forces, for instance using a sharing force assumption during the double support phase of gait [4]. Another approach consists in keeping external forces and varying kinematics and the torso's center of mass position, such as the Residual Reduction Algorithm (RRA) in OpenSim [5]. Finally, other strategies consider changing both kinematics and external forces with a least square estimation [6].

This paper presents an optimal control algorithm for solving the dynamic inconsistency problem, *i.e.*, minimizing the residual actuators, at the price of introducing variations to the measured kinematics. The proposed algorithm is tested against a previous published solution by Alvim *et al.* [3], which uses RRA.

METHODS

Reference motion, joint torques and ground reaction forces (GRF) from 6 healthy subjects performing the single leg triple hop (SLTH) test, as well as their respective scaled OpenSim skeletal models, were taken from [3] before applying the RRA. The preparatory phase of the SLTH test, a relatively high-speed and torque-demanding task, was used to compare the presented algorithm with that applied in [3].

The proposed residual reduction procedure was formulated as an optimal control problem that tracked reference data. Joint coordinates and velocities were states of the problem ($\mathbf{x}^T = [\mathbf{q}, \dot{\mathbf{q}}]$), and joint accelerations and torques were introduced as controls ($\mathbf{u}^T = [\ddot{\mathbf{q}}, \boldsymbol{\tau}]$). The cost functional consisted of the minimization of squared differences between design variables ($\mathbf{x}, \mathbf{u}$) and their respective reference data ($\mathbf{x}_{ref}^T = [\mathbf{q}_{ref}, \dot{\mathbf{q}}_{ref}], \mathbf{u}_{ref}^T = [\ddot{\mathbf{q}}_{ref}, \boldsymbol{\tau}_{ref}]$). Moreover, to ensure that the stance foot did not slip in the optimal solution found, an additional term tracking three points along that segment was added. Those three points ($\mathbf{p}_{ref}$) were introduced as virtual markers equidistantly positioned between the heel and the big toe, and its corresponding position ($\mathbf{p}$) computed from the state variables was added to track them.

$$[MIN]\ J = \int_{t_0}^{t_f} (\mathbf{x} - \mathbf{x}_{ref})^T \boldsymbol{W}_{\mathbf{x}} (\mathbf{x} - \mathbf{x}_{ref}) + (\mathbf{u} - \mathbf{u}_{ref})^T \boldsymbol{W}_{\mathbf{u}} (\mathbf{u} - \mathbf{u}_{ref}) + (\mathbf{p} - \mathbf{p}_{ref})^T \boldsymbol{W}_{\mathbf{p}} (\mathbf{p} - \mathbf{p}_{ref})\, \mathrm{d}t \tag{1}$$

being $\boldsymbol{W}_{\mathbf{x}}$, $\boldsymbol{W}_{\mathbf{u}}$ and $\boldsymbol{W}_{\mathbf{p}}$ diagonal weight matrices**.** Moreover, a set of constraints were considered, employing the implicit form of dynamics [7]. First, dynamic constraints were applied to ensure time derivative relationships among kinematic variables:

$$\begin{bmatrix} \dot{\mathbf{q}} \\ \ddot{\mathbf{q}} \end{bmatrix} = \frac{\mathrm{d}}{\mathrm{d}t} \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix} \tag{2}$$

An inverse dynamic analysis (IDA) was solved to obtain the joint torques ($\boldsymbol{\tau}_{IDA}$) and residuals ($\mathbf{R}_{IDA}$), using design variables related to motion ($\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}$) and imposing experimental GRF ($\mathbf{GRF}_{exp}$). Two path constraints were introduced. The first, equaling control torques ($\boldsymbol{\tau}$) to the resulting torques of the IDA ($\boldsymbol{\tau}_{IDA}$). The second, limiting the residuals ($\mathbf{R}_{IDA}$) within an interval of tolerances ($\boldsymbol{\varepsilon}_{R}$) set to ±2 N and ±2 Nm, respectively:

$$\boldsymbol{\tau} - \boldsymbol{\tau}_{IDA}\left(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, \mathbf{GRF}_{exp}\right) = \mathbf{0} \tag{3}$$

$$-\boldsymbol{\varepsilon}_{R} \leq \mathbf{R}_{IDA}\left(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, \mathbf{GRF}_{exp}\right) \leq \boldsymbol{\varepsilon}_{R} \tag{4}$$

The optimal solution reported in this study was obtained using GPOPS-II [8] and IPOPT [9]. Also, OpenSim API was called during the optimization to solve the IDA.

In order to assess results and compare both algorithms, the reduced residuals and the obtained joint coordinates were contrasted with the corresponding results presented in [3]. Furthermore, the mean and standard deviation of the root-mean-square (RMS) of the residuals for each subject were calculated.

RESULTS

Before applying the reduction algorithms, residual forces and moments presented the highest average RMS values over 90 N and 90 Nm, and the lowest values of almost 17 Nm (Table 1, left column). After applying the optimal control algorithm, residuals were reduced within the limits set on the problem, being the maximum RMS of 1.91 N in the vertical residual force. Moreover, standard deviations in all components presented results under 0.4 N or Nm, indicating small variability between the different subjects (Table 1, middle column).

Furthermore, differences were appreciated depending on the residual reduction procedure used. Reductions obtained performing the RRA changed depending on the residual component, having a reduction of 95% in the vertical force but a reduction of 12% in the mediolateral moment (Table 1, right column). In the case of the proposed algorithm, reductions were above 90% in all components. Also, applying the RRA maintained bounded residual values before starting the ascending phase of the test, but higher values once the subject was ascending. Contrarily, residuals were kept within the range of ±2 N and ±2 Nm during the entire task, when the presented residual reduction approach was used (Figure 1).

[TABLE 1]

[FIGURE 1]

Joint coordinates after applying the optimal control algorithm manifested a very similar evolution than the reference motion until 50% of the task, moments prior starting the ascending phase of the test. As soon as the ascending phase started, some coordinates showed a different behavior from the captured motion, being the pelvis tilt and lumbar extension coordinates the ones that differed the most. At 50% of the task, pelvis tilted anteriorly slower than the captured motion and then, at 75%, faster. On the other hand, torso started to extend at 50% of the task, contrarily to the reference coordinate, which started at 80% of the task (Figure 2). Compared to the motion obtained from the RRA, changes in kinematics were in general higher. Nevertheless, coordinates such as pelvis list or left ankle flexion presented lower RMS error. Overall, considering the six subjects, the mean RMS error of angular coordinates was 1.33^{o} for the RRA solution and 1.97^{o} for the optimal control solution.

[FIGURE 2]

DISCUSSION & CONCLUSIONS

This study presented an approach to reduce residual forces and moments based on optimal control theory. Tracking reference data while introducing experimental GRF allowed the algorithm to successfully reduce the residual actuators during the preparation phase of the SLTH test, a high-speed and torque-demanding task. Compared to the residual reduction performed in [3] applying RRA, it can be concluded that lower values of residual components were reached using the presented method. Introducing the residuals as a constraint, instead of adding them to the cost function, allowed always to fulfill the tolerances set on the problem, even in tasks involving high torque efforts. Additionally, low variability among the results for each subject was obtained.

The reduction was achieved by varying the reference kinematics obtained from the measurements. It was observed that coordinates that changed the most were the ones that may have had more effect on changing the pose of the body segments with higher inertia. Hence, the dynamic consistency was achieved by the modified kinematics, which allowed to compensate both modelling and experimental errors. Note that unlike RRA in OpenSim, the proposed optimal control method does not change the torso center of mass position to reduce residuals, which yields larger changes in kinematics with respect to the reference motion than in RRA. Nevertheless, the solution presented in this study shows that the discrepancy in terms of RMS error, which has an overall mean of 1.93^{o}, is similar to the maximum values tolerated in previous published motion tracking studies [10, 11].

The higher changes in kinematics and the need of imposing experimental GRF could be denoted as two limitations of the algorithm. Depending on the initial residuals and the kinematics of the task, the final motion could change in a manner that would produce unrealistic movements, such as slipping or losing ground contact with the stance foot. Consequently, if the algorithm relies on the experimental GRF, it must include constraints or a term in the cost function (such as in this study, the additional foot tracking term) to avoid these issues. Conversely, incorporating a foot-ground contact model would directly produce realistic movements and GRF that would be dynamically consistent.

In conclusion, this study contributed to introduce a suitable approach to reduce residuals that presented satisfactory results in a high-speed and torque-demanding task. Hence, it could be used as a complementary tool for other optimal control algorithms that simulate new motions, relying on dynamically consistent data. Furthermore, future work is contemplating the adaptation of the presented algorithm to develop a foot-ground contact model, which at the same time, will be introduced to improve the performance of the proposed method.

CONFLICTS OF INTEREST

The authors disclose that there are no financial and personal relationships with other people or organizations which could inappropriately influence this work.

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LIST OF FIGURES

Figure 1. Comparison of residual force and moment components of one subject after performing the reduction through the optimal control problem (black line) and the RRA in [3] (grey line). Residual forces (F) and moments (M) are expressed in anatomical directions: Anteroposterior (AP), Vertical (V) and Mediolateral (ML).

Figure 2. Evolution of joint coordinates after applying the optimal control algorithm (black lines) and the RRA in [3] (grey lines) compared to the reference motion (dashed black lines) for one subject. Each plot presents the RMS error (RMSE) between the obtained joint coordinates and the reference motion performing the optimal control algorithm (black) and the RRA (grey).

FIGURES

Both gray-scale, no need for color.

Figure 1:

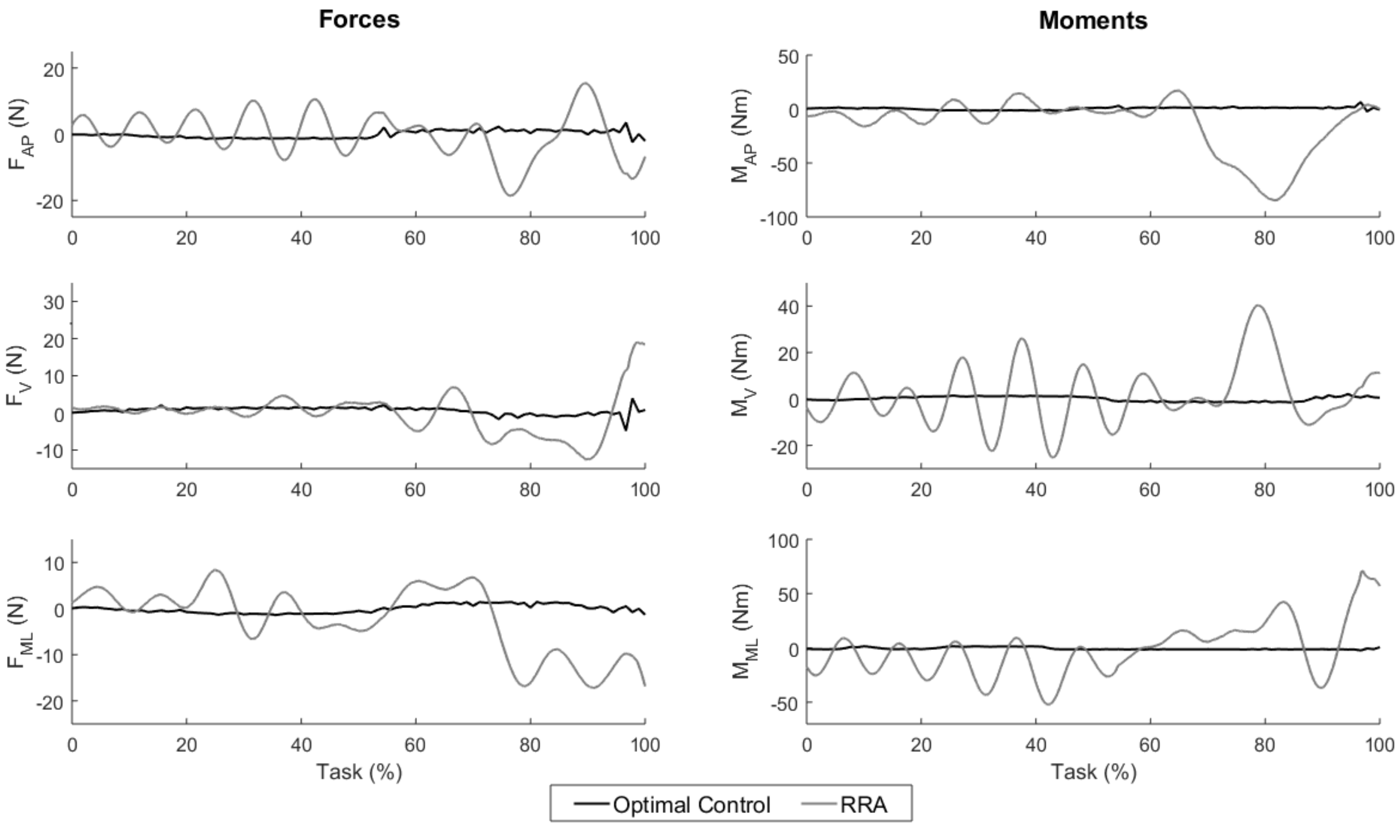

Figure 2: