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Optimization-based Dynamic Human Lifting Prediction

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ABSTRACT

In this study, an optimization-based approach for simulating the lifting motion of a three dimensional digital human model is presented. Lifting motion is generated by minimizing a performance measure subjected to basic physical and kinematical constraints. Two performance measures are investigated: one is the dynamic effort; the other is the compression and shear forces on the lumbar joint. The lifting strategies are predicted with different performance measures. The joint strength (torque limit) and the compression and shear force on lumbar joint are also addressed in this study to avoid injury during lifting motion.

INTRODUCTION

The lifting biomechanics of humans is an important issue in many industrial applications. In human lifting, many strategies may be chosen to suit the task, e.g., weight, position, and shape of an object. Two major solutions have been referred in the literature (Chaffin and Andersson, 1991): the squat lift and the back lift. However, most biomechanists quantify the lifting strategy purely on kinematics or several parameters in the model. The whole-body dynamic lifting motion has not been fully investigated, especially the effects of the shear and compression forces on lumbar vertebra, which in many cases results back pain and injury (Pope and Novotny, 1993).

Kinematic lifting simulation was widely conducted in the literature (Matsunaga et al., 2004; Zhang et al., 2000). The basic idea was to quantify the lifting strategy to certain indexes. However, the whole-body dynamic lifting motion was not fully considered in these approaches. The use of dynamic simulation models in investigating the lifting task, has recently evolved as a valuable technique that provides insight into the analysis of lifting motion. Huang et al. (2005) developed a multibody dynamics model to generate optimal trajectories of human lifting movements based on optimal control. The muscle activation parameters were treated as inputs instead of joint torques. The optimal motion was generated to minimize the loading of specific joints such as an ankle, or a knee during the lifting motion and subject to space-time constraints. Arisumi et al. (2007) studied the dynamic lifting motion of humanoid robots which considered the instantaneous transferred load to the object as an impulsive force.

In the present work, an optimization-based predictive dynamics formulation is developed to predict natural lifting motion. A program based on a sequential quadratic programming approach is used to solve the nonlinear optimization problem. Two performance measures are investigated: one is the dynamic effort that is represented as the time integral of the squares of all the joint torques; the other is the compression and shear forces on the lumbar joint. The dynamic stability is achieved by satisfying the zero moment point (ZMP) constraint throughout the lifting motion. In addition to predict the natural motion, the effects of joint strength (torque limit) and the compression and shear force on the lumbar joint are also addressed in the formulation to avoid injury during the lifting process.

SPATIAL HUMAN SKELETAL MODEL

The kinematics of the spatial human skeletal model is based on the Denavit-Hartenberg method (Denavit and Hartenberg, 1955).

55-DOF WHOLE-BODY MODEL

A spatial digital human skeletal model with 55 DOFs, as shown in Figure 1, is considered in this work. The model consists of six physical branches and one virtual branch. The physical branches include the right leg, the left leg, the spine, the right arm, the left arm, and the head. In these branches, the right leg, the left leg, and the spine start from the pelvis, while the right arm, left arm, and head start from the ending joint of the spine. The virtual branch contains six global DOFs, including three global translations and three global rotations that move the model from the origin (o-xyz) to the current pelvic position.

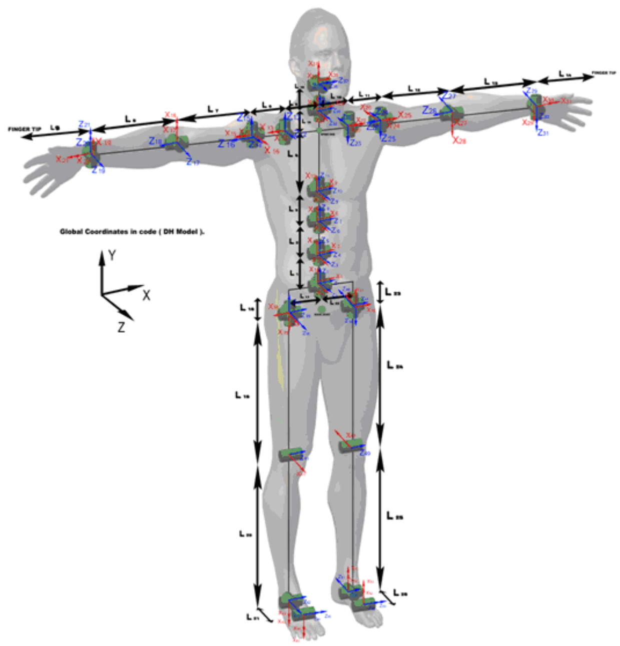


Figure 1. The digital human model based on DH method

DYNAMICS MODEL

RECURSIVE LAGRANGIAN FORMULATIONS

Recursive Lagrangian equations of motion are adopted in this study because of their well-known computational efficiency. The whole-body dynamics are considered in the formulation as well as ground reaction forces. The recursive formulation includes two parts: forward kinematics and backward dynamics. Forward kinematics start from the root joint and propagate the recursive position, velocity, and acceleration matrixes based on the link transformation matrix and the kinematics state variables for each joint.

Based on forward recursive kinematics, the backward dynamics transfer the inertia and Coriolis forces, gravity, and external forces backward to the root joint. In addition, the gradients of the force for the spatial human mechanical system with respect to the state variables $\frac{\partial \tau_i}{\partial q_k}, \frac{\partial \tau_i}{\partial \dot{q}_k}, \frac{\partial \tau_i}{\partial \ddot{q}_k}$ (i = 1 to n; k = 1 to n) can be evaluated in a recursive way using the recursive Lagrangian formulations (Xiang et al., 2008).

GROUND REACTION FORCES

The ground reaction forces (GRF) are considered in the motion and evaluated from the global equilibrium. A two-step algorithm is used to calculate GRF as depicted in the following flowchart.

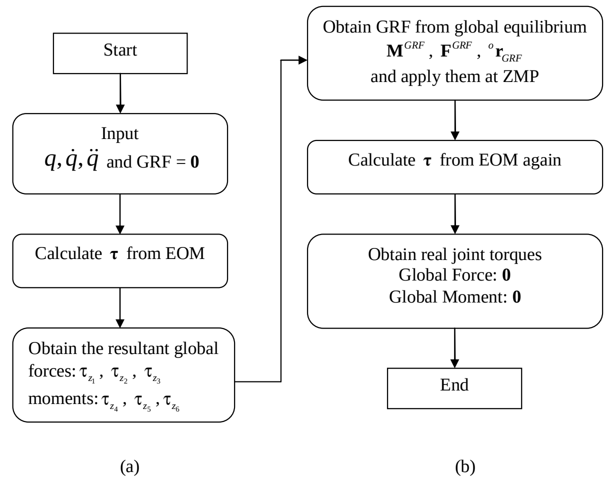


Figure 2. Flowchart of two-step algorithm to calculate GRF (a) without GRF, and (b) with GRF

The basic idea is to retrieve GRF from equilibrium between the passive GRF and the resultant active forces (inertial force, gravity, and external loads) in equations of motion (Xiang et al., 2007).

LIFTING MODEL

LIFTING TASK

In this work, the lifting task is defined as moving a box from an initial location to a final location. Figure 3 depicts the input parameters for the proposed formulation. In this regard, h_1 is the initial height of the box measured from the ground, d_1 is the initial distance measured from the foot location to the center of the box; h_2 is the final height measured from the ground, d_2 is the final distance, and w is the weight of the box. The initial and final postures and dynamic lifting trajectory are solved from a nonlinear optimization problem. In addition, the mechanical system is at rest at the initial and final times.

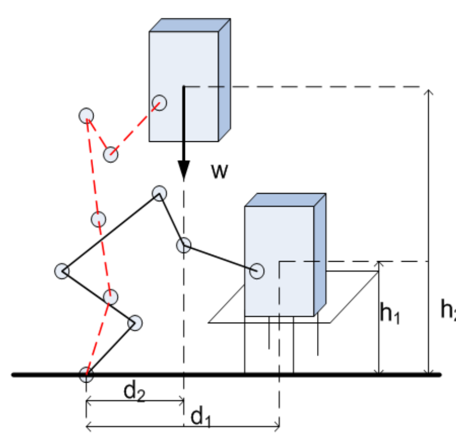


Figure 3. Input parameters for lifting task

NONLINEAR PROGRAMMING

The lifting task is formulated as a general nonlinear programming problem. To find the optimal lifting trajectories **q**, a human performance measure is minimized and subject to physical constraints as follows:

$$\begin{aligned} &\textbf{Find: } \mathbf{q} \\ &\textbf{To: } \min f(\mathbf{q}) \\ &\textbf{Sub. } \mathbf{h}_i = \mathbf{0}\ ;\ i = 1, \ldots, m \\ &\qquad \mathbf{g}_j \le \mathbf{0}\ ;\ j = 1, \ldots, k \end{aligned} \tag{1}$$

where $\mathbf{h}$ is the equality constraint and $\mathbf{g}$ is the inequality constraint.

OPTIMIZATION FORMULATION

DESIGN VARIABLES

In the current formulation, the design variables are the joint profiles $q_i(t)$ for the lifting motion. The torque profiles are calculated from joint profiles using the recursive Lagrangian dynamics equations.

OBJECTIVE FUNCTION

Two objective functions $f(\mathbf{q})$ are investigated in this study: one is the dynamic effort, the integral of the torque squares of all joints over time (Eqn. 2); the other is the integral of squares of the compression and shear forces on the lumbar joint (Eqn. 3).

$$f_1 = \int_{t=0}^{T} \boldsymbol{\tau}(\mathbf{q}) \cdot \boldsymbol{\tau}(\mathbf{q})\, dt \tag{2}$$

where τ_i is active joint torque for the i^{th} joint.

$$f_2 = \int_{t=0}^{T} \left(F_x^2 + F_y^2 + F_z^2\right) dt \tag{3}$$

where F_x is lateral shear force on the lumbar joint, F_z is forward shear force on the lumbar joint, and F_y is compression force on the lumbar joint.

CONSTRAINTS

A general constraint library is developed in Virtual Soldier Research Program (VSR™) predictive dynamics environment. The advantage of using a constraint library is that some constraints can be shared for various tasks. For the lifting task, joint limits, torque limits, ground penetration, foot locations, and ZMP stability, are common constraints shared with walking, running, stair climbing and so on. The hand orientation, vision, collision avoidance, and initial and final box locations are new constraints for the lifting problem.

In the vision constraint (Eqn. 4), the vision vector is aligned towards the box center. In the hand orientation constraint (Eqn. 5), the two hands are positioned normal to the box to facilitate the appropriate grasping postures. The collision avoidance constraint (Eqn. 6) is used to keep the box from penetrating the body. These constraints are illustrated in Figure 4.

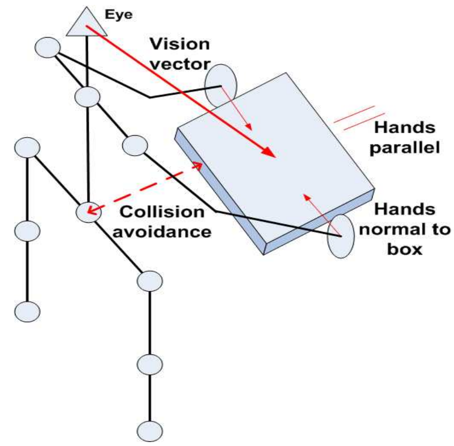
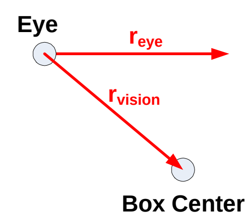


Figure 4. Hand orientation, vision, and collision avoidance constraints

Vision Constraint

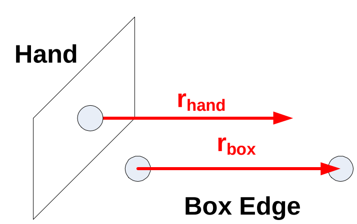
The vision constraint makes the eye vector align with the vision vector.



$$\mathbf{r}_{\text{eye}} \cdot \mathbf{r}_{\text{vision}} = 0 \tag{4}$$

Hand Orientation

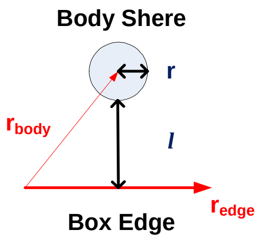
The hand normal vector aligns with the box.



$$\mathbf{r}_{\text{hand}} \cdot \mathbf{r}_{\text{box}} = 0 \tag{5}$$

Collision Avoidance

Santos is filled with spheres on the ankle, knee, hip, shank, thigh, chest, and neck with various radiuses to represent body thickness. The distance between box edge and sphere center is measured to impose collision avoidance.



$$d = \left\| \frac{\mathbf{r}_{\text{body}} \times \mathbf{r}_{\text{edge}}}{\left\| \mathbf{r}_{\text{edge}} \right\|} \right\| \geq r + l \qquad (6)$$

NUMERICAL RESULTS

For the optimization problem, the entire time domain is discretized by B-spline curves. The joint angles are represented by the discretized control points **P**. Hence, the continuous optimization problem is transformed into nonlinear programming optimization (NLP). A large-scale sequential quadratic programming (SQP) approach in SNOPT (Gill et al., 2002) is used to solve this problem.

Four control points are used for each DOF and thus we have 4×55 = 225 design variables and 420 nonlinear constraints. Each case requires about 200 CPU seconds on a Pentium(R) 4 3.46 GHz computer.

MINIMIZING DYNAMIC EFFORT

In this section, the first objective function, the dynamic effort, will be introduced. In this formulation, the foot locations and time duration are specified for a lifting task. Given the box initial location (d_1=0.4 m, h_1=0.4 m), final location (d_2=1.0 m, h_2=0.3 m), and weight (w=10 lbs), the dynamic lifting motion is predicted to minimize the performance measure, dynamic effort, and subject to physical constraints. In this case, the torque limit on lumbar joint is considered 100 Nm. Figure 5 shows the resulting optimal lifting motion. As expected, correct bending of the knee and spine occur to generate the optimal lifting motion. This is a typical *back lift* which is successfully predicted by the current formulation.

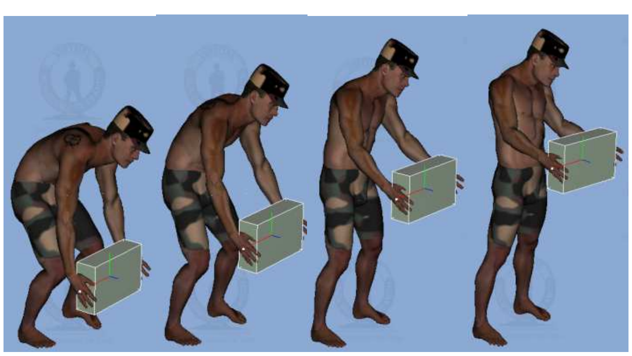


Figure 5. Sequential snapshots of Santos moving a 10 lb box from a lower shelf to a higher shelf

To study cause-and-effect, the torque limit on the lumbar joint is reduced from the previous 100 Nm to the current 50 Nm. The same lifting task is optimized with the reduced torque limit, and the optimal lifting motion is obtained as follows:

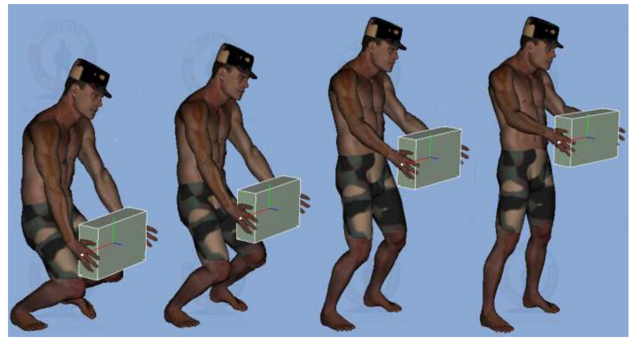


Figure 6. Sequential snapshots of Santos moving a 10 lb box from a lower shelf to a higher shelf with reduced lumbar torque limit

In the lifting process, the spine remains upright to reduce the lumbar torque and a *squat lift* strategy is adopted with the reduced torque limits on the lumbar joint. In addition, the spine bending torque for the squat lift and back lift are compared in Figure 7. It is evident that the back lift results in a larger torque value on the lumbar joint.

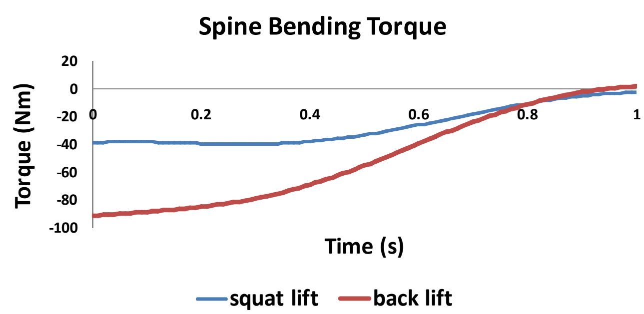


Figure 7. Lumbar torque profile for squat lift and back lift

MINIMIZING LUMBAR FORCES

In this section, the second objective function, the lumbar forces, is minimized in the lifting motion. Using the same input parameters as in the previous section, the lifting motion is optimized to minimize lumbar shear forces and compression force.

<u>Case 1: Minimizing lumbar shear force</u>

The optimal lifting motion of minimizing the lumbar shear forces is depicted in Figure 8.

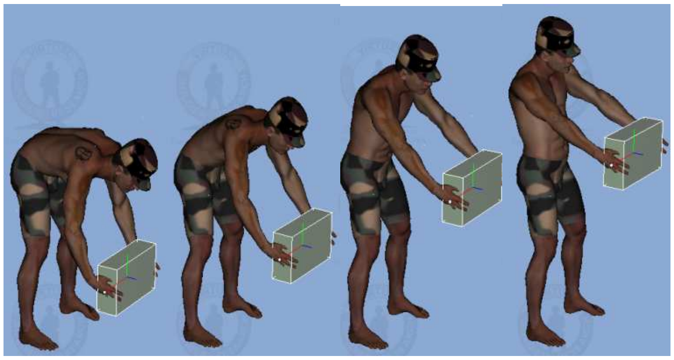


Figure 8. Sequential snapshots of Santos moving a 10 lb box from a lower shelf to a higher shelf by minimizing lumbar shear forces

The compression and shear forces on the lumbar joint are plotted in Figure 9.

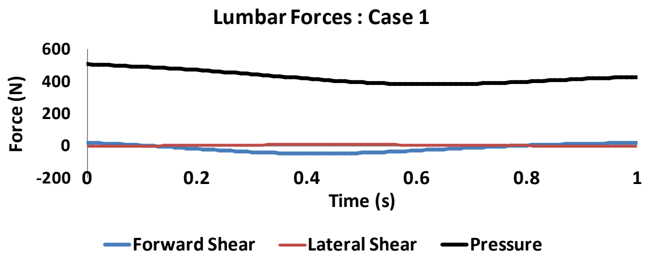


Figure 9. Lumbar forces for case 1

Minimizing shear forces results in a very symmetric lifting motion as shown in Figure 8. The maximum forward shear force is -48.3 N, the lateral shear force is 7.56 N, and the compression force is 453.4 N. This motion indeed gives smaller shear forces, but results in large compression force.

<u>Case 2: Minimizing lumbar compression force</u>

The optimal lifting motion of minimizing the lumbar compression force is shown in Figure 10.

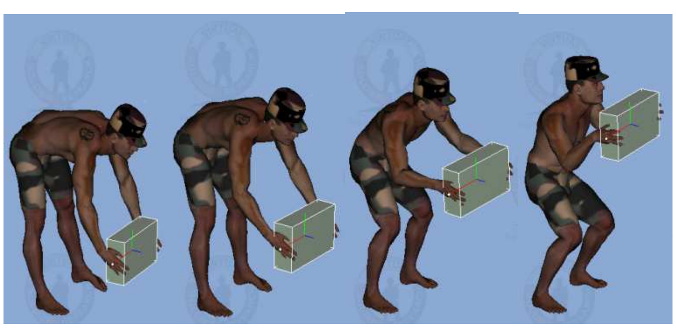


Figure 10. Sequential snapshots of Santos moving a 10 lb box from a lower shelf to a higher shelf by minimizing lumbar compression force

It is interesting to note that Santos chooses a smart strategy to lift the box to minimize lumbar compression. Santos first uses a back lift, then bends the knees and raises the hands to move the box to the final location. The lumbar compression and shear forces are illustrated in Figure 11.

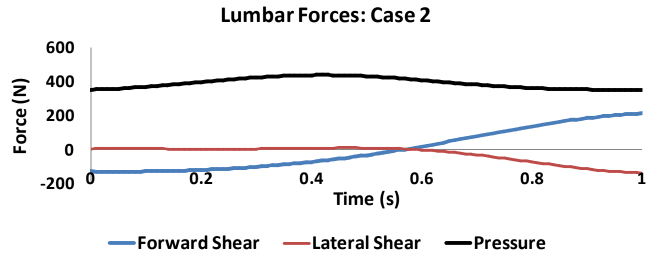


Figure 11. Lumbar forces for case 2

The maximum forward shear force is 128.9 N, the lateral shear force is -137.4 N, and the compression force is 435.8 N. It can be seen that minimizing lumbar compression results in larger shear forces, but relatively smaller compression force.

CONCLUSION

In this study, lifting motion prediction was presented and some insights on lifting strategy were analyzed. The motion planning was formulated as a large-scale nonlinear programming problem. Joint profiles were discretized using cubic B-splines, and the corresponding control points were treated as unknowns. Two objective functions were used in the lifting formulation: dynamic effort and lumbar forces. Based on the simulation data, the results have demonstrated the ability of the proposed methodology to choose a realistic human lifting strategy with different objective functions and constraints. The effect of lumbar torque limit on lifting motion was studied, and the back lift and squat lift were predicted based on the torque limit. Kinetic data such as joint torque and lumbar forces were also analyzed. The dynamic lifting motion prediction has a wide variety of applications for biomechanics, ergonomics and human pathology analyses. It is also a robust prototype design tool, e.g., it can be used to study a specific joint injury problem by reducing the corresponding torque limit. Moreover, the lifting strategies can be predicted with different performance measures. Finally, the motion-capture-based validation of the current formulation is ongoing, and the simulation results may be further improved with validation feedback.

ACKNOWLEDGMENTS

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