EVALUATION OF A PATIENT-SPECIFIC COST FUNCTION TO PREDICT THE INFLUENCE OF FOOT PATH ON THE KNEE ADDUCTION TORQUE DURING GAIT

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1. ABSTRACT

A large external knee adduction torque during gait has been correlated with the progression of knee osteoarthritis (OA). Though foot path changes (e.g., toeing out) can reduce the adduction torque, no method currently exists to predict whether optimal foot path exists for a specific patient. This study evaluates a patient-specific optimization cost function to predict how foot path changes influence both adduction torque peaks. Video motion and ground reaction data were collected from a patient with knee OA performing normal, toe out, and wide stance gait. Joint and inertial parameters in a dynamic, 27 degree-of-freedom, full-body gait model were calibrated to the patient's normal gait data. The model was then used in gait optimizations that predicted how the patient's adduction torque peaks would change due to changes in foot path. The cost function tracked the patient's normal gait data using weight factors calibrated to toe out gait and tested using wide stance gait. For both gait motions, the same cost function weights predicted the change in both adduction torque peaks to within 7% error. With further development, this approach may eventually permit the design of patient-specific rehabilitation procedures such as an optimal foot path for patients with knee OA.

2. INTRODUCTION

As computational technologies continue to improve, dynamic musculoskeletal models may eventually permit optimization of functional outcome for surgical or rehabilitative interventions on an individual patient basis. An important step toward this goal is the development of musculoskeletal models that match key features of the patient's anatomy and movement characteristics. These features include 1) the kinematic structure of the patient, as represented by the types, positions, and orientations of functional axes in the body segments (Bogert et al., 1994; Reinbolt et al., 2005), 2) the inertial properties of the patient, as indicated by segment masses, mass centers, and moments of inertia (de Leva, 1996; Rao et al., 2006), and 3) the control strategy used by the patient (Buchanan et al., 2004; Bottasso et al., 2005; Liu et al., 2005;). If all three features could be calibrated to pre-treatment movement data collected from a patient,

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the calibrated model could be used to optimize functional outcome for the various treatment scenarios and parameters under consideration.

This study investigates whether a patient-specific optimization cost function based on external gait measurements can be used to predict how changes in foot path affect the external knee adduction torque during gait. Since the magnitude of this torque has been positively correlated with the progression of medial compartment knee osteoarthritis (OA) (Baliunas et al., 2002; Miyazaki et al., 2002), rehabilitation treatments that lower this torque may be useful for slowing the progression of knee OA. The patient-specific cost function is defined by adjustable weight factors on error terms that track a patient's normal kinematic and kinetic gait data. The goal is to find weights such that minimization of the cost function produces the patient's knee adduction torque curve for gait motions with altered foot paths. The work presented here is the first step toward the development of a computational approach for designing patient-specific rehabilitation procedures, such as an optimal foot path for patients with knee OA.

3. METHODS

3.1 Experimental gait data

Experimental gait data were collected from a patient with knee OA (male, age 40 years, height 170 cm, mass 69 kg) using a video based motion analysis system with modified Cleveland Clinic marker set (Motion Analysis Corporation, Santa Rosa, CA) and two force plates (AMTI, Watertown, MA). The modification involved adding three markers to each foot segment to allow three-dimensional tracking of the feet. Institutional review board approval and informed consent were obtained prior to the experiments. For all trials, the patient walked at a self-selected speed of 1.4 m/s. Unloaded isolated joint motions were performed to exercise the primary functional axes of each lower extremity joint (hip, knee, and ankle on each side). For each joint, the patient was instructed to move the distal segment within the physiological range of motion so as to exercise all degrees of freedom (DOFs) of the joint (Reinbolt et al., 2005). Gait motion and ground reaction data were collected to provide simultaneous motion of all lower extremity joints under load bearing physiological conditions. One cycle (i.e., left heel strike to left heel strike) of three different gait motions (normal, toe out, and wide stance) was analyzed to produce a range of different knee adduction torque curves for testing the predictive capabilities of the proposed patient-specific cost function.

3.2 Patient-specific gait model

A dynamic, patient-specific gait model was developed to predict new gait motions and loads given experimental data for the patient's normal gait motion. The full-body model is three dimensional and possesses 27 degrees of freedom (DOFs) (Fig. 1). The equations of motion for the model were derived using two different methods - the symbolic manipulation software Autolev™ (OnLine Dynamics, Sunnyvale, CA) and the musculoskeletal modeling software SIMM with the Dynamics Pipeline (Motion Analysis Corporation, Santa Rosa, CA), thereby allowing us to verify the accuracy of the equations. Comparable to Anderson and Pandy's (2001) model structure, 3 translational and 3 rotational DOFs express the movement of the pelvis in the laboratory reference frame, and the remaining 13 segments comprise four open chains branching from the pelvis. The kinematic structure of the model is defined by joint parameters that designate the positions and orientations of joint axes within adjacent segment coordinate systems. The kinematic structure utilizes the following joint types: 3 DOF hip, 1 DOF knee (with external reaction torque calculated for adduction), 2 DOF ankle (nonintersecting axes; Bogert et al., 1994), 3 DOF back, 2 DOF shoulder, and 1 DOF elbow. The inertial properties of the model are defined by inertial parameters that designate each segment's mass, mass center along its longitudinal axis, and three central principal moments of inertia. All joint and inertial parameters in the model were calibrated to the patient's normal gait data and isolated joint motion experiments.

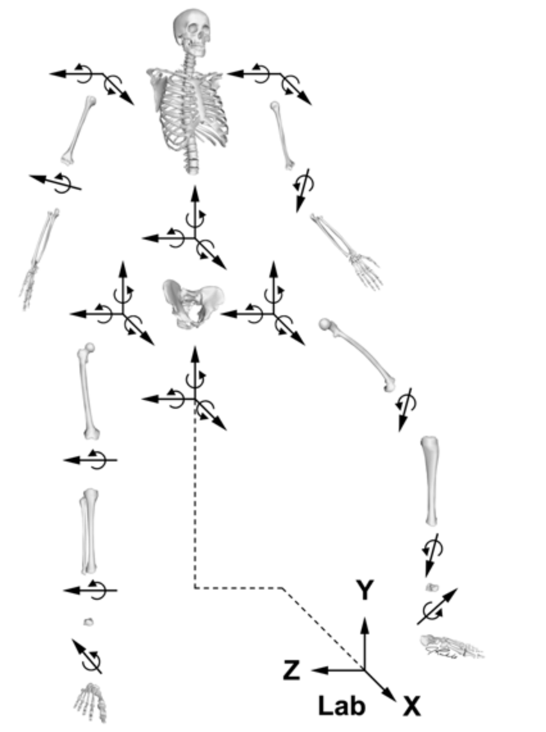

Figure 1: Schematic of patient-specific dynamic gait model used in the optimization studies.

For the subsequent predictive gait optimizations, inverse rather than forward dynamics simulations were performed with the calibrated model (Mazza and Cappozzo, 2004), thereby eliminating stability problems due to the use of open-loop joint torque controls. Inputs to the inverse dynamics model were values of the 27 generalized coordinates, their first and second time derivatives, and bilateral ground reaction forces and torques, while outputs were 27 joint torques (including six residual forces and torques acting on the pelvis), bilateral foot paths (not generalized coordinates), trunk orientation (also not generalized coordinates), and bilateral centers of pressure. Ground reactions were set to zero during periods when the foot was known to be in contact with the floor. The pelvis residual loads, which represent errors in the model's structure, parameters, and/or experimental inputs, were driven close to zero through calibration of the model's joint and inertial parameters.

3.3 Patient-specific cost function

To predict changes in the patient's knee adduction torque due to changes in foot path, we constructed an optimization cost function containing weight factors that were calibrated to the patient's toe out gait data and then tested using his wide stance gait data. The proposed cost function assumes that different gait motions produced by the same patient will be neighboring solutions of one another. For example, we do not expect the joint motions and torques from a patient's toe out gait motion to be markedly different from those of his normal gait motion. Thus, we assume that a patient's normal gait data provides a good initial guess for how he will walk under other conditions. This assumption leads to the formulation of an optimal tracking problem, where the cost function minimizes a weighted sum of squares of changes in kinematic and kinetic quantities away from the patient's normal gait data. If the correct weights are placed on the various quantities in the cost function, then ideally the optimization will predict how the patient would walk under conditions for which experimental data are not available.

The cost function weights were calibrated to the patient's toe out gait data by solving a two-level optimization problem. The outer-level optimization varied the weights used by the inner-level cost function so as to minimize errors between experimental and predicted adduction torque peaks for toe out gait. Given the current guess for weights from the outer level, the inner-level optimization varied the shape of the input motion and ground reaction curves so as to minimize the weighted sum of squares of errors between experimental (normal gait with adjusted foot path) and predicted (toe out gait) kinematic and kinetic quantities. The outer-level optimization utilized a univariate search algorithm developed by the author (Fregly et al., 2005) while the inner-level optimization utilized Matlab's nonlinear least squares algorithm.

Once the inner-level cost function weights were calibrated to the patient's toe out gait data, they were tested using his wide stance gait data. Testing required only the inner-level optimization, with three new foot path offsets being calculated to convert the patient's normal foot path into a wide stance foot path that best matched his wide stance gait data. Thus, while calibration required repeated inner-level optimizations to determine the inner-level cost function weights, testing required only a single inner-level optimization to evaluate how well the same cost function weights could predict both adduction torque peaks for a different gait motion.

4. RESULTS

After the cost function weights were calibrated to the patient's toe out gait data, the inner-level optimization produced close predictions of both knee adduction torque peaks. The first adduction torque peak was matched to within 7% error and the second peak to within 3% (Fig. 2a). The primary kinematic change observed experimentally, which was an increase in hip external rotation, was also well predicted. However, not all kinetic changes observed experimentally were reproduced by the optimization. While the decrease in hip abduction torque half way through the gait cycle was well predicted, the decrease in hip extension torque near the start of the cycle and the increase in knee extension torque over much of stance phase were not. The optimization predicted little change in ground reaction forces, consistent with experimental observations. It also predicted little change in the anterior-posterior center of pressure trajectory and a gradual lateral shift in the medial-lateral center of pressure trajectory, both consistent with experimental findings.

When the same cost function weights were tested using the patient's wide stance gait data, the inner-level optimization again produced close predictions of both knee adduction torque peaks. The first adduction torque peak was predicted to within 7% error and the second peak to within 6% (Fig. 2b). Unlike for toe out gait, the primary kinematic changes observed experimentally were not well predicted, these being an increase in hip and knee flexion over the first half of the cycle. While the hip extension torque was well predicted, the optimization again did not predict the increase in knee extension torque during stance phase. Little change in the ground reaction forces was again predicted, though the predicted increase in medial force was less than that observed experimentally. Finally, the optimization predicted little change in the anterior-posterior center of pressure trajectory and a fixed lateral offset in the medial-lateral center of pressure trajectory, both highly consistent with experimental findings.

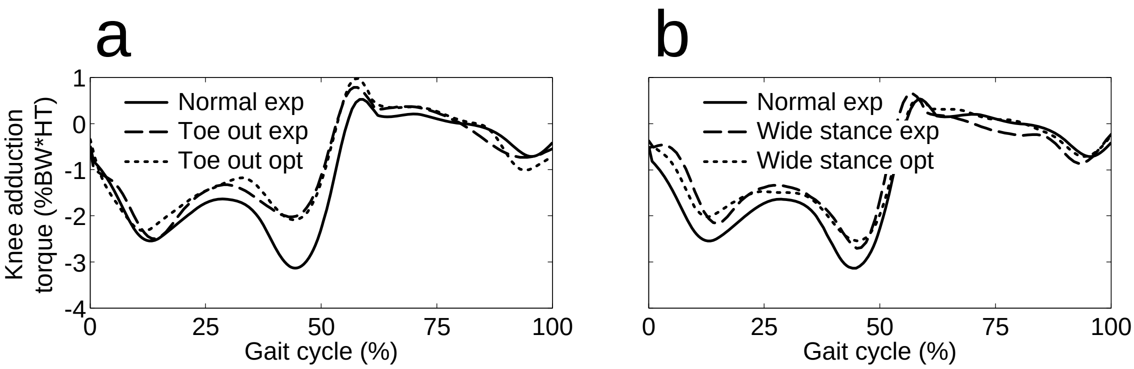

Figure 2: Evaluation of left knee adduction torque curves predicted using the patient-specific optimization cost function. a) Toe out gait prediction for which the cost function weights were calibrated. b) Wide stance gait prediction for which the cost function weights were tested.

5. DISCUSSION

This study evaluated whether a patient-specific optimization cost function in conjunction with a patient-specific gait model can be used to predict how foot path changes will affect the patient's knee adduction torque. The optimization was formulated as an optimal tracking problem, where the cost function minimized the weighted sum of squares of changes away from the patient's nominal gait data. The cost function weights were calibrated to predict the patient's toe out gait adduction torque peaks and then tested by predicting his wide stance gait peaks. After calibration, a single set of cost function weights successfully predicted both adduction torque peaks to within 7% error for both toe out and wide stance gait. Many kinematic and kinetic changes (or lack thereof) were also predicted well by the optimizations (e.g., the lateral shift in the center of pressure), though some changes observed experimentally were not reproduced (e.g., the increase in knee extension torque). Thus, while the proposed cost function accurately predicted the quantity for which it was calibrated, it did not predict all potential quantities of interest accurately. Nonetheless, these initial results suggest that with future developments, a similar approach may make it possible to design rehabilitation or surgical treatments so as to maximize functional outcome for the individual patient.

The ability of a single set of cost function weights to predict the patient's adduction torque peaks for two different gait motions suggests that our initial hypothesis about neighboring solutions was reasonable. One possible outcome was that no cost function weights could be found that successfully predicted both adduction torque peaks for toe out gait starting from the patient's normal gait motion. Another possibility was that the calibrated weights successfully predicted both adduction torque peaks for toe out gait but not wide stance gait. It was therefore encouraging that a single set of weights predicted both adduction torque peaks to within 7% error for two different foot paths, including one for which the weights were not calibrated.

Despite this result, the calibrated weights did not yield accurate predictions for all kinematic and kinetic quantities from the two gait motions with modified foot paths. This finding may indicate limitations in the model structure, errors in the model parameters, or (most likely) the need for refinement in the cost function formulation. Two obvious refinements are worthy of future investigation. The first would be to put different weights on the different leg control torques, since different muscle groups possess different strength properties. The second would be to eliminate the need to use a normal data set for tracking purposes. Calibrating the cost function weights to a single data set, as done in several recent studies (Bottasso et al., 2005; Liu et al., 2005), could also address the limitation that the current cost function formulation does not have an obvious physical interpretation tied to a hypothesized neural control strategy.

6. ACKNOWLEDGMENTS

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