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Benjamin J. Fregly
University of Florida

Jonathan P. Walter
University of Florida

Allison Kinney
University of Dayton, akinney2@udayton.edu

Scott A. Banks
University of Florida

Darryl D. D'Lima
Scripps Clinic

See next page for additional authors

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Author(s)

Benjamin J. Fregly, Jonathan P. Walter, Allison Kinney, Scott A. Banks, Darryl D. D'Lima, Thor F. Besier, and David G. Lloyd

MUSCLE SYNERGIES IMPROVE ESTIMATION OF KNEE CONTACT FORCES DURING WALKING

**Benjamin J. Fregly (1), Jonathan P. Walter (1), Allison L. Kinney (1), Scott A. Banks (1),
Darryl D. D’Lima (2), Thor F. Besier (3), and David G. Lloyd (4)**

(1) Dept. of Mechanical & Aerospace Eng.
University of Florida
Gainesville, FL, USA

(2) Shiley Center for Orthopaedic Res. & Ed.
Scripps Clinic
La Jolla, CA, USA

(3) Auckland Bioengineering Institute
University of Auckland
Auckland, NZ

(4) School of Rehabilitation Sciences
Griffith University
Gold Coast, QLD, AU

INTRODUCTION

Knowledge of patient-specific muscle and joint contact forces during activities of daily living could improve the treatment of movement-related disorders (e.g., osteoarthritis, stroke, cerebral palsy, Parkinson’s disease). Unfortunately, it is currently impossible to measure these quantities directly under common clinical conditions, and calculation of these quantities using computer models is limited by the redundant nature of human neural control (i.e., more muscles than theoretically necessary to actuate the available degrees of freedom in the skeleton). Walking is a particularly important task to understand, since loss of mobility is associated with increased morbidity and decreased quality of life [1]. Though numerous musculoskeletal computer modeling studies have used optimization methods to resolve the neural control redundancy problem, these estimates remain largely unvalidated due to the lack of internal force measurements that can be used for validation purposes.

This study investigates whether use of subject-specific muscle synergies can improve optimization predictions of muscle excitation patterns and knee contact forces during walking. Muscle synergies describe how a small number of neural commands generated by the nervous system can be linearly combined to produce the broad range of muscle electromyographic (EMG) signals measured experimentally. By quantifying the interdependence of individual EMG signals, muscle synergies provide dimensionality reduction for the neural control redundancy problem. Our hypothesis was that use of subject-specific muscle synergies to limit muscle excitation patterns would improve prediction of muscle EMG patterns at the hip, knee, and ankle and of contact forces at the knee using a subject-specific lower body musculoskeletal computer model. The predictions were evaluated against in vivo experimental data collected from a subject implanted with a force-measuring tibial prosthesis.

METHODS

Walking data were collected from a subject implanted with a force-measuring tibial prosthesis (female, age 69 yrs, height 167 cm, weight 78.4 kg, neutral leg alignment, knee replacement for primary knee osteoarthritis). Institutional review board approval and subject informed consent were obtained. The following types of data were collected from the subject: video motion capture from reflective surface markers on the arms, torso, pelvis, thighs, shanks, and feet; ground reaction force and moment from three force plates; surface EMG from 13 hip, knee, and ankle muscles in the implanted leg; and tibial contact force and moment from an instrumented tibial prosthesis [2]. Medial and lateral contact forces were calculated from six-axis tibial load cell data using calibrated regression equations ($R^2 = 0.99$) developed using a deformable contact model of the subject’s implant components [3]. A single trial of the subject’s normal walking pattern was selected for analysis. All data used in this study are from the Third Grand Challenge Competition to Predict In Vivo Knee Loads and are freely available from <https://simtk.org/home/kneeloads> [3].

A subject-specific full-leg (pelvis to foot) musculoskeletal model was constructed in OpenSim [4] using full-leg CT scan data collected from the subject. Image processing and reverse engineering software, along with CAD models of the subject’s implant components, were used to construct implant-bone surface models of the subject’s pelvis, femur with femoral component, patella with patellar button, tibia with tibial tray and insert, fibula, and talus, with scaled foot geometry taken from a published OpenSim model [5]. The hip was modeled as a three degree-of-freedom (DOF) ball-and-socket joint, the tibiofemoral and patellofemoral joints as 6 DOF free joints, and the ankle as two non-intersecting pin joints. Muscle origins, insertions, and wrapping surfaces from the same scaled published OpenSim model [5] were transferred to the closest anatomic locations on our model.

The subject-specific OpenSim model was used to estimate leg muscle and knee contact forces using a novel static optimization approach. Two different categories of optimization problems were formulated, both of which minimized the sum of squares of 44 muscle excitations. The first category (called “Match” cases) tracked 8 experimental inverse dynamics loads (3 at the hip, 3 at the knee – flexion moment, adduction moment, and superior force, and 2 at the ankle) and 13 processed EMG signals. The six-axis knee loads measured by the instrumented implant where applied to the tibia and femur so that tracked inverse dynamic knee loads accounted for contributions from knee contact forces. Thus, the first category matched the experimental medial and lateral knee contact forces and processed EMG signals by design. The second category (called “Predict” cases) tracked 6 experimental inverse dynamics loads (3 at the hip, 1 at the knee – flexion moment only, and 2 at the ankle) with no tracking of EMG data. This category predicted medial and lateral knee contact forces along with processed EMG signals.

Muscle excitations for both categories were modeled two ways. The first method (called “Independent”) parameterized each of the 44 muscle excitations independently using B-splines. The second method (called “Synergy”) used non-negative matrix factorization [6] to decompose the 13 mutually dependent processed EMG signals into 6 independent neural command signals with corresponding weights that accounted for 95% of the variability in the original processed EMG signals. Thus, neural commands rather than muscle excitations were parameterized with B-splines, and the corresponding synergy weights were also treated as parameters. In both cases, muscle activation [7] and contraction [8] dynamics were modeled by discretizing the relevant first-order ordinary differential equations describing the EMG-to-activation and activation-to-force processes.

This methodology resulted in four optimization problem formulations: 1) Predict/Independent, 2) Predict/Synergy, 3) Match/Independent, and 4) Match/Synergy. Design variables were muscle excitation curve parameters, excitation scaling parameters, activation dynamics parameters (pure time delay, activation time constant, deactivation time constant), contraction dynamics parameters (peak isometric force, optimal muscle fiber length, tendon slack length, tendon stiffness), muscle moment arm parameters (B-spline curves defining small offsets to nominal moment arm curves), and tibiofemoral anterior-posterior (AP) translation parameters (B-spline curve defining AP translation profile). All four optimization problems were solved using Matlab’s lsqnonlin nonlinear least squares algorithm. In addition to minimizing excitations and tracking inverse dynamic load (and possibly EMG) curves, the cost function minimized changes in activation and contraction dynamics parameter values away from literature values [5].

RESULTS

Both Predict cases were able to reproduce all experimental inverse dynamics loads ($R^2 = 0.97 \pm 0.00$) and EMG profiles ($R^2 = 0.83 \pm 0.10$) with good accuracy. Corresponding medial and lateral knee contact forces calculated from the regression equations were also in excellent agreement with experimental measurements ($R^2 = 0.96 \pm 0.01$). Results were equally good for the Independent and Synergy formulations. In contrast, for the Predict cases, the Synergy formulation produced better knee contact force predictions ($R^2 = 0.88 \pm 0.00$ vs. $R^2 = 0.78 \pm 0.04$, Fig. 1) and muscle excitation predictions ($R^2 = 0.29 \pm 0.27$ vs. $R^2 = 0.09 \pm 0.50$) than did the Independent formulation. However, prediction of experimental EMG profiles for both formulations was worse than desired. Furthermore, optimized parameter values were frequently different between corresponding Match and Predict cases.

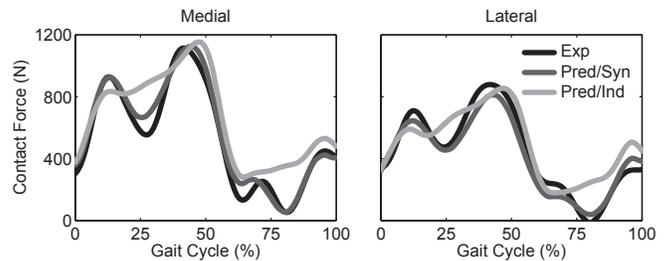


Fig. 1: Comparison between experimental and predicted knee contact forces.

DISCUSSION

This study investigated the extent to which muscle synergy information can be used to limit optimization predictions of muscle excitation patterns and knee contact forces during walking. The fact that both Match formulations reproduced all relevant experimental measurements well indicated that the model possessed the potential to perform well for the Predict cases using both excitation schemes. The fact that the Predict/Synergy formulation did not produce large R^2 values for excitations suggests that synergies did not limit predicted excitation patterns as much as anticipated.

There are at least three explanations for this unexpected outcome. First, only the shape and not the amplitude of the experimental EMG signals has meaning. To address this issue, processed EMG signals are typically normalized, in our case to maximum value over the selected walking cycle. This amplitude limitation also carries over to the calculated neural command signals. For this reason, an excitation scaling parameter was required for each muscle to scale its maximum excitation. Second, insufficient limitations were placed on normalized muscle lengths predicted by the model. In each of the four optimization formulations, several muscles had normalized lengths that were less than 0.5 during a portion of the walking cycle, turning off the muscle’s force production in that region. A recent study reported that normalized muscle lengths remain above 0.5 during walking [9], suggesting that some adjustment to our optimization problem formulation is needed. Third, model parameter values were likely inadequately calibrated for the Predict cases, since some calibrated parameter values were significantly different from those found by the Match cases. Specific calibration trials may be needed to improve estimation of critical model parameter values that affect predicted muscle excitations in particular.

Despite these limitations, the knee contact forces predicted in this study were extremely close to the experimental measurements. Future refinements of our methodology will seek to predict knee contact forces and muscle excitation patterns that both follow experimental measurements closely.

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