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A Surrogate Model for Lower Extremity EMG-to-Moment Estimation during Walking

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SUMMARY
The clinical impact of neuromusculoskeletal models is limited by the difficulty of calibrating musculotendon and moment arm parameter values to patient movement data. To address this limitation, we created a numerical technique called "surrogate moment estimation" (SME) that predicts net joint moments at the hip, knee, and ankle directly from electromyographic (EMG) and kinematic data. SME uses a large quantity of redundant motion trials to calibrate a polynomial response surface that represents a muscle's moment generating properties. The surrogate model is able to predict sagittal plane hip, knee, and ankle moments accurately during walking and produces physiologically consistent muscle contributions to net joint moments. This modeling technique could be used to drive neuromusculoskeletal walking models without calibrating musculotendon and moment arm parameter values for individual muscles.

INTRODUCTION
Computer modeling of the human neuromusculoskeletal system has the potential to improve the diagnosis and treatment of movement related disorders such as stroke and osteoarthritis. To be used for this purpose, such models need to be customized to the anatomic and neurological characteristics of individual patients. Current techniques for customizing models to patient movement data are often arduous and unable to calibrate weakly observable model parameter values, such as those related to muscle moment arms and muscle force generation [1].

This study presents surrogate moment estimation (SME), a novel method for estimating net joint moments directly from a patient's processed EMG and kinematic data for periodic activities such as walking [2]. SME uses a polynomial response surface surrogate model in place of explicit Hill-type muscle models with geometric lines of action. Parameters of SME models can be easily determined using optimization and linearize algebra without the need for MRI or other imaging data.

METHODS
EMG (Motion Lab Systems, Baton Rouge, LA), video motion (Vicon Corp., Oxford, UK), and ground reaction force data were collected simultaneously from a single healthy male subject performing normal walking at 1.2 m/s on an instrumented split-belt treadmill (Bertec Corp., Columbus, OH). Institutional review board approval was obtained, and the subject gave informed consent. One hundred fifty trials of normal walking were selected for model calibration, and fifty trials were withheld for model evaluation. Surface EMG signals were collected from thirteen muscles: Gluteus Maximus, Gluteus Medius, Rectus Femoris, Vastus Medialis, Vastus Lateralis, Adductor Magnus, Biceps Femoris, Semitendinosus, Semimembranosus, Tibialis Anterior, Medial and Lateral Gastrocnemius, and Soleus.

EMG data were processed according to previously published methods [3]. EMG signals were high pass filtered at 30 Hz, demeaned, positively rectified, and low pass filtered at 6 Hz. Each processed EMG signal was normalized to its maximum value over all walkings trials analyzed.

Hip, knee, and ankle joint moments and kinematics were calculated from marker motion and ground reaction force data using a 27 degree-of-freedom full-body inverse dynamics walking model. Mass properties and joint axis locations in the model were calibrated to the subject's video motion and ground reaction data [4]. For each gait trial, an inverse kinematics analysis was performed to determine joint angles during gait. The calibrated inverse dynamics model was used to calculate sagittal plane moments at the hip, knee, and ankle at 101 normalized time points in the gait cycle. For consistency with the EMG data, net joint moments from inverse dynamics were filtered at 6 Hz with a 4th order zero phase lag Butterworth filter [3].

Muscle activations were calculated from the processed EMG signals using a finite difference approximation of a linear first order differential equation representing EMG-to-activation dynamics [5]:

$$\frac{da(t)}{dt} = [c_1\varepsilon(t) + c_2]\big(\varepsilon(t) - a(t)\big) \qquad (1)$$

where a is activation, ε is the EMG value, $c_1 = 1/\tau_{act} - c_2$, $c_2 = 1/\tau_{deact}$, τ_{act} and τ_{deact} are the muscles' activation and deactivation time constants, t is time in the

gait cycle. We solved this equation over an entire gait cycle by discretizing it using a central difference approximation:

$$-\left(\frac{1}{2\Delta t}\right)a_{i-1} + c_3 a_i + \left(\frac{1}{2\Delta t}\right)a_{i+1} = c_3\varepsilon_i\,,\;\; c_3 = c_1\varepsilon_i + c_2 \quad (2)$$

where Δt represents the time step and a_i and ε_i are the EMG and activation values at a discretized time point in the gait cycle. Equation (2) was applied to each time point i in the gait cycle, and the resulting linear system of equations was solved for all a_i values. A correction for activation nonlinearities during periods of low excitation was also included [6]. Activation parameter values were determined by an optimization that maximized moment prediction accuracy while minimizing non-physiological muscle moment contributions (e.g., a flexor muscle should only contribute a flexor moment). The optimization also determined a fixed time delay for each muscle of 0 to 50 ms and included an EMG scaling parameter since maximum EMG is difficult to determine experimentally.

Numerous gait trials were used to solve a linear system of equations that implicitly accounted for muscle moment arms and muscle force-length-velocity properties. For each muscle, a linearized Hill-type muscle model was used to approximate sagittal plane EMG-to-moment relationships at the hip, knee, and ankle [7]:

$$M(\theta,\dot{\theta}) = \sum_{i=1}^{m}\{a_i[c_{i1} + c_{i2}\theta + c_{i3}\theta^2 + c_{i4}\dot{\theta} + c_{i5}\theta\dot{\theta}]\} \quad (3)$$

where $M(\theta,\dot{\theta})$ represents the net joint moment, θ and $\dot{\theta}$ are normalized joint angles and velocities, m is the number of muscles that contribute to the moment, and a_i is the activation of muscle i. In this model, c_{i1} is an offset term, c_{i2} and c_{i3} represent muscle force-length properties, c_{i4} represents muscle force-velocity properties, and c_{i5} represents a force-length-velocity interaction. For bi-articular muscles, parameters $c_{i6} - c_{i9}$ were added to represent the effects of the respective neighboring joints on the muscle's force-length-velocity properties. Coefficients in this model were first solved separately for each joint via linear least squares (5 parameter values for 13 muscles determined using 150 gait trials). Then Matlab's nonlinear least squares optimizer modified these initial parameter values to constrain each muscle to produce moments only in physiological directions. Parameters for activation dynamics were held constant for each muscle.

We evaluated our technique using two measures - accuracy of total moment predictions and physiological consistency of individual muscle moment contributions. First, we calibrated our model using 150 trials of normal gait. Then we used the calibrated parameter values to predict the joint moments and individual muscle moment contributions for the 50 test trials. Median RMS errors and R^2 values for the net joint moment predictions were calculated, and individual muscle contributions to net joint moments were evaluated.

RESULTS AND DISCUSSION

For the 50 test trials, predicted hip, knee, and ankle moments were highly accurate (Fig. 1 top), and individual muscle moments were generated almost exclusively in physiological directions (Fig. 1 bottom). The hip, knee, and ankle predictions had median R^2 values of 0.95, 0.97, and 0.97, respectively, and RMS errors of 0.53, 0.21, and 0.38 %BWHt. The individual muscle moment contributions for the ankle and knee are nearly perfectly physiological, with only a few muscles producing small moments in non-physiological directions. At the hip, Rectus Femoris and Adductor Magnus produced moments that were probably too large for these muscles, likely due to the omission of Illiapsoas.

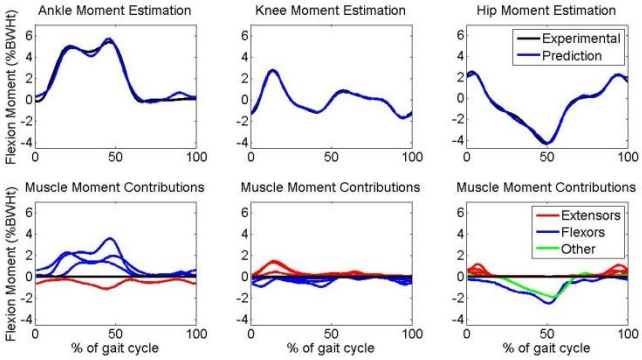

Figure 1: Ensemble average moment predictions compared with experimental moments (top) and individual muscle contributions to net moments (bottom)

While SME was able to produce accurate muscle moments with physiological individual muscle contributions, several important limitations exist. SME is limited primarily by the need for a large number of motion trials to calibrate model parameter values. Additionally, SME may only work for periodic motions such as gait. We did not collect EMG data for several important muscles, including Vastus Intermedius and Illiopsoas. Inclusion of more muscles in our model will likely improve the accuracy of our predictions.

CONCLUSIONS

SME may prove to be a valuable tool for dynamic simulation of periodic motions. Only a small number of coefficients are needed for each muscle to model moment generation from processed EMG data. The method negates the need for explicit geometric musculoskeletal models incorporating individual musculotendon models whose parameter values are difficult if not impossible to calibrate accurately for individual patients. Since moments are calculated quickly and easily with SME, it may be possible to incorporate SME into predictive gait optimizations to determine optimal walking patterns for patients with neural impairments.

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