INTRODUCTION

Application of neuromusculoskeletal models to clinical problems will likely require model customization to the unique anatomical and neurological conditions of each patient. Unfortunately, current modeling methods make model customization to patient data difficult, especially for model parameter values related to muscle-tendon actuators and musculoskeletal geometry [1]. Improved methods are needed so that patient-specific neural control capabilities and limitations can be easily incorporated into predictive gait optimizations to be used for intervention planning purposes.

This study presents a novel statistical method for predicting net joint moments directly from electromyographic (EMG) and kinematic data. The method could allow measured or simulated muscle EMG signals to control dynamic skeletal models directly without the need for explicit Hill-type muscle-tendon models or complex musculoskeletal geometry. In this study, we describe the approach for generating an over-determined system of equations for statistical EMG-to-moment estimation, and we present an initial evaluation of the approach using the knee flexion-extension moment during gait.

METHODS

Video motion (Vicon Corp., Oxford, UK), EMG (Motion Lab Systems, Baton Rouge, LA), and ground reaction data were recorded simultaneously from a single healthy subject walking on an instrumented split-belt treadmill (Bertec Corp., Columbus, OH). Institutional review board approval and subject informed consent were obtained. The subject walked at a speed of 1.2 m/s while performing his normal gait pattern (125 cycles) and a toe-out gait pattern (50 cycles). Surface EMG data were collected from eight muscles: gastrocnemius medialis and lateralis, rectus femoris, vastus medialis and lateralis, biceps femoris, semimembranosus, and semitendonosis.

EMG data were processed in a manner similar to previously published methods [2]. Raw EMG signals were high-pass filtered at 30 Hz, demeaned, rectified, and finally low-pass filtered at 6 Hz. After these steps, each EMG signal was normalized to maximum value over all gait cycles.

Knee flexion moment, angle, and angular speed were calculated using a customizable 27 degree-of-freedom (DOF) full-body dynamic walking model. Model Properties were calibrated to the subject’s video motion and ground reaction data using previously published optimization methods [3]. For each of the 150 gait cycles, an inverse dynamics analysis was performed with the calibrated subject-specific model to calculate the knee flexion-extension moment at 51 normalized time points across the gait cycle. Joint motions required for inverse dynamics were obtained via inverse kinematics performed with the calibrated model.

Figure 1: Graphical portrayal of the statistical moment estimation method.

To turn processed muscle EMG signals and knee kinematics into a knee flexion-extension moments, we developed a novel computational method called “statistical moment estimation” (SME). SME is different from existing EMG-to-moment estimation methods (e.g., [4]) in that model parameter values are constant only at normalized time points in a motion cycle rather than across the motion cycle (Fig. 1). To obtain unique model parameter values at each normalized time point, we collect at least twice as many motion cycles as unknown model
parameter values. Since gait is a periodic motion, we assume that kinematic and kinetic conditions at each joint vary within a small range at each normalized time point. We then employ the Taylor series concept from mathematics to define how the joint moment to be estimated varies away from its operating point as a function of local changes in EMG patterns and kinematics.

For this initial evaluation of SME, we linearized the mathematical form of a Hill-type muscle model to derive the following approximate EMG-to-moment relationship:

\[
M(\theta, \dot{\theta}, t) = \left( \sum_{i=1}^{8} \frac{\varepsilon_i}{e_i} - \frac{\varepsilon_i}{e_i - 1} [c_i + c_{i2}\theta + c_{i3}\theta^2 + c_{i4}\theta^3] \right) + [c_5 + c_6\theta]
\]

(1)

In this equation, \(\varepsilon_i\) represents the processed EMG signal for muscle \(i\), \(t\) represents time, \(\tau\) represents a constant EMG-to-activation time delay (50 ms based on [2]), \(A_i\) is a nonlinear EMG-to-activation exponent for muscle \(i\) that ranges between -3 and 0 [2], \(\theta\) is the knee flexion angle, \(\dot{\theta}\) is the knee flexion angular speed, \(c_1\) through \(c_4\) are constants accounting for force-length, and force-velocity properties for muscle \(i\), and \(c_5\) and \(c_6\) are passive force-length terms for all muscles lumped together. The \(c\) coefficients are mathematically constrained to vary smoothly between time frames.

We performed two evaluations of our proposed SME method using the 150 knee flexion-extension moment curves calculated from the treadmill gait data. Each evaluation followed a “calibrate-test” approach, where 100 gait cycles were used to solve Eq. (1) at the 51 normalized time points in the gait cycle, and then the resulting model parameter values were used to test the estimated knee flexion moments using 25 additional gait cycles. The first evaluation used 100 normal gait cycles for calibration and the remaining 25 normal gait cycles for testing, while the second evaluation used 75 normal and 25 toe-out gait cycles for calibration and 25 toe-out gait cycles for testing. We used Matlab’s fmincon optimizer to make repeated guesses for \(A_i\) \((i = 1, \ldots, 8)\) while the cost function used the current guesses and linear regression to solve for the best-fit coefficients \(c_{ij}\) \((i = 1, \ldots, 8, j = 1, 2, 3)\), \(c_5\), and \(c_6\).

RESULTS AND DISCUSSION

Overall, the knee flexion moment curves predicted by SME were reasonably accurate for normal and toe-out gait (Fig. 2). RMS prediction errors were 3.1 Nm for normal gait and 3.9 Nm for toe-out gait.

The knee flexion-extension moment estimates generated in this study suggest that the statistical moment estimation idea has merit. Moment estimates were reasonable for toe-out gait, even though the calibration was performed primarily using normal gait data. This fact shows that the method may be able to predict the knee flexion moment for subjects with erratic or asymmetric gait patterns, such as subjects who have had a stroke.

Our proposed statistical EMG-to-moment estimation method possesses several advantages as well as disadvantages. On the positive side, the model to be fitted in Eq. (1) is very simple with a low number of parameters, allowing for unique determination of model parameter values at any normalized time frame given enough gait cycles. SME also eliminates the need for explicit muscle-tendon models and complex musculoskeletal geometry. Thus, SME could permit measured or simulated EMG signals to control dynamic skeletal models directly, simplifying incorporation of patient-specific neural control capabilities and limitations directly into predictive gait optimizations. On the negative side, each fitted SME model will only be accurate for a specific normalized time point in the gait cycle. Also, the method will only work for periodic motions, and it requires a large number of motion cycles to formulate an over-determined system of equations at each normalized time point in the motion cycle.

REFERENCES


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