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Lumped-parameter electromyogram-driven musculoskeletal hand model: A potential platform for real-time prosthesis control

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ABSTRACT

Simple, lumped-parameter musculoskeletal models may be more adaptable and practical for clinical real-time control applications, such as prosthesis control. In this study, we determined whether a lumped-parameter, EMG-driven musculoskeletal model with four muscles could predict wrist and metacarpophalangeal (MCP) joint flexion/extension. Forearm EMG signals and joint kinematics were collected simultaneously from 5 able-bodied (AB) subjects. For one subject with unilateral transradial amputation (TRA), joint kinematics were collected from the sound arm during bilateral mirrored motion. Twenty-two model parameters were optimized such that joint kinematics predicted by EMG-driven forward dynamic simulation closely matched measured kinematics. Cross validation was employed to evaluate the model kinematic predictions using Pearson's correlation coefficient (r). Model predictions of joint angles were highly to very highly positively correlated with measured values at the wrist (AB mean $r=0.94$, TRA $r=0.92$) and MCP (AB mean $r=0.88$, TRA $r=0.93$) joints during single-joint wrist and MCP movements, respectively. In simultaneous multi-joint movement, the prediction accuracy for TRA at the MCP joint decreased ($r=0.56$), while r-values derived from AB subjects and TRA wrist motion were still above 0.75. Though parameters were optimized to match experimental sub-maximal kinematics, passive and maximum isometric joint moments predicted by the model were comparable to reported experimental measures. Our results showed the promise of a lumped-parameter musculoskeletal model for hand/wrist kinematic estimation. Therefore, the model might be useful for EMG control of powered upper limb prostheses, but more work is needed to demonstrate its online performance.

1. Introduction

Computational musculoskeletal models have been used extensively to investigate healthy and impaired human movement (Higginson et al., 2006; Zajac et al., 2002) and simulate surgery and rehabilitation (Delp et al., 1990; Saul et al., 2003; Shelburne and Pandy, 1998), among other applications. Forward dynamic simulation, when applied to musculoskeletal models, can generate joint kinematic predictions from input electromyogram (EMG) signals. Forward dynamic simulation has primarily been used offline, for example, to estimate muscular biomechanical contributions to movement (Neptune et al., 2001) and joint loading (Manal and Buchanan, 2013). When executed in real-time, forward dynamic simulation could generate motion predictions for external devices, such as powered prostheses (Eilenberg et al., 2010).

Many upper limb musculoskeletal models implemented for real-time EMG-driven forward dynamic simulation include numerous musculoskeletal elements to accurately represent anatomy and generate physiologic predictions. Model complexity has ranged from 5 muscles and 1 degree of freedom (DOF) to predict isometric elbow joint moments (Manal et al., 2002), to 138 muscles and 11 DOFs to investigate the complex motions of the arm and shoulder girdle (Chadwick et al., 2009). Unfortunately, it may be impractical to adapt anatomically-representative models for real-time clinical control applications, as an overwhelming number of parameters would need to be customized. Adjusting models parameters for amputees is even more challenging since (1) there is no intact musculoskeletal structure from which to measure parameters directly, and (2) the perceived biomechanical actions associated with EMG signals are not observable and may be altered from that of a healthy, intact limb due to cortical reorganization (Ramachandran and Hirstein, 1998). Measuring EMG for several muscles, especially deep muscles, may also be clinically challenging and subject to crosstalk. Finally, forward dynamic simulation of models with several musculoskeletal elements can be computationally intensive.

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As a counter to complex models, lumped-parameter models that combine the action of several muscles into fewer muscle elements may be more clinically practical (Eilenberg et al., 2010; Lehman and Calhoun, 1990; Messier et al., 2011). Modeling fewer muscle elements reduces (1) the number of parameters that must be adjusted for each subject, (2) the number of input EMG signals, and (3) the computational burden of forward dynamic simulation. To streamline the development of subject-specific models, researchers have used numerical optimization to adjust existing or define novel parameters to minimize error between measured and predicted joint *moments* given input EMG signals (Lehman and Calhoun, 1990; Lloyd and Buchanan, 1996; Shin et al., 2009). However, methods based on joint moments cannot be applied for amputees since the moments in the missing joints are indeterminable. Though both motion and force mirroring have been used as an indicator of amputee movement intent (Kamavuako et al., 2012; Muceli and Farina, 2012), force may not be truly mirrored since amputees cannot actively resist external loads on their amputated side. Therefore, we propose to compute a novel set of musculoskeletal parameters for a lumped-parameter model to match measured joint *kinematics*.

The objective of our pilot study was to develop and preliminarly test a lumped-parameter, 2 DOF model of the hand. Specifically, we wanted to (1) demonstrate that the model could reasonably predict joint kinematics during single-joint and simultaneous two-joint movements for able-bodied subjects and a transradial amputee; (2) compare the active and passive joint moment-generating capacity of subjects' models to that reported for healthy, intact limbs; and (3) evaluate the performance and repeatability of numerical optimization for computing model parameters. Our findings may promote the development and translation of real-time musculoskeletal model-based forward dynamic simulation for multifunctional upper limb prosthesis control.

2. Methods

2.1. Experiments and data collection

Experiments were approved by the institutional review board. Five able-bodied (AB1-AB5) subjects (3 males, 2 females, age range 23–31 years) and 1 subject (TRA) with transradial amputation (male, age 42) provided informed consent to participate. Subject TRA sustained a right traumatic amputation approximately 2 years before participating, and regularly used a body-powered prosthesis.

In one session, subjects performed 5 different types of movement in a static upper limb posture with the arm and forearm in neutral posture and elbow flexed to 90°: (1) wrist flexion/extension only, variable speed; (2) MCP flexion/extension only, variable speed; (3) simultaneous wrist and MCP flexion/extension, variable speed; (4) wrist flexion/extension only, fixed speed; and (5) MCP flexion/extension only, fixed speed. During *variable speed* movements, subjects moved in self-selected speeds and directions. In *fixed speed* trials, subjects alternated between maximum extension, relaxed, and maximum flexion joint postures at a regulated tempo (0.25 Hz). Able-bodied subjects performed the movements with the dominant arm, while subject TRA mirrored movements bilaterally. Each movement type was tested in two trials for at least 30 s; each subject performed a total of 10 trials (5 movements x 2 trials/movement). Subjects rested between trials.

During trials, EMG and kinematic data were collected synchronously from able-bodied subjects' dominant limb; for subject TRA, EMG and kinematics were measured from the residual and sound limb, respectively. Four bipolar surface EMG electrodes (Biometrics, Newport, UK) were placed over muscles/muscle groups (Fig. 1) identified by anatomical reference and palpation during experimenter-directed movements, and confirmed by visualizing EMG. The selected muscles generate wrist and metacarpophalangeal (MCP) flexion and extension joint moments in intact limbs based on their musculoskeletal geometry (Perotto, 2005). EMG data were sampled at 960 Hz, high-pass filtered at 40 Hz, rectified, enveloped, and low-pass filtered at 6 Hz using a 4th order Butterworth zero-phase filter, similar to previous methods (Lloyd and Besier, 2003). EMG were then normalized by respective maximum (post-processed) EMG signal values recorded during maximum voluntary contractions.

Given the short length of subject TRA's residual limb, EMG associated with wrist flexion appeared in electrodes targeting both wrist and MCP flexion, as flexor digitorum (MPC flexion) is deep to flexor carpi ulnaris (wrist flexion) in the proximal forearm. Therefore, similar to a previous method (Reddy and Gupta, 2007), we linearly transformed MCP flexor EMG ($EMG_{MCPflex}$)to reduce EMG associated with wrist flexion, based on the approximate proportion of wrist flexor EMG ($EMG_{wristflex}$) appearing in $EMG_{MCPflex}$ during isolated wrist flexion movements (Eq.1):

$$EMG^{*}_{MCPflex} = EMG_{MCPflex} - 0.75EMG_{wristflex} \tag{1}$$

Reflective markers were placed on 9 anatomical locations to track distal limb motion (Fig. 1); thumb motion was not recorded or included in the model. Three-dimensional marker positions were recorded at 120 Hz using an infrared motion capture system (Vicon Motion Systems Ltd., UK), and filtered at 6 Hz using a 4th order Butterworth filter. Wrist and MCP joint angles were computed from filtered marker data using a musculoskeletal model (Holzbaur et al., 2005a) in OpenSim (Delp et al., 2007) that was modified to include the 2nd through 5th MCP joints.

2.2. Dynamic hand model

We defined a planar link-segment dynamic model (dynamic properties described in Supplementary Data) with two degrees of freedom (DOFs) - wrist and MCP flexion/extension – that was encoded in MATLAB (MathWorks, Inc., Natick, MA). Four muscles, one for each EMG source, were represented as Hill-type actuators with a contractile element (*CE*) and parallel elastic element (*PEE*) (Winters, 1990). A series elastic element, commonly included in Hill-type models to represent tendon, was not included. The force output of the contractile element, F^{CE}, was a function of its length (L^{CE}), shortening velocity (v^{CE}), and state of activation (a) (Eq. 2).

$$F^{CE} = f(L^{CE})f(v^{CE})a \tag{2}$$

where $f(L^{CE})$ is the active *CE* force (Eq. 3) and $f(v^{CE})$ is a hyperbolic scaling function that reduces F^{CE} as v^{CE} increases (Eq. 4).

$$f(L_{CE}) = F_0^{CE}\left(1 - \frac{(L^{CE} - L_0^{CE})^2}{W^2 (L_0^{CE})^2}\right) \qquad f(L^{CE}) > 0.01 \tag{3}$$

$$f(v_{CE}) = \frac{v^{CE}_{max} - v^{CE}}{v^{CE}_{max} + \left(\frac{v^{CE}}{c}\right)} \qquad 0 < f(v^{CE}) < 1 \tag{4}$$

In Eq. 3, L_0^{CE} is the optimal *CE* length, and w, which defined the range over which the *CE* could produce force as a fraction of L_0^{CE}, was set at 0.5 (Buchanan et al., 2004). In Eq. 4 the maximum *CE* shortening velocity (v^{CE}_{max}) was set to 10 $\frac{L_0^{CE}}{s}$, and the hyperbolic shape factor (c) was set to 0.25 (Winters, 1990; Zajac, 1989). The parallel elastic element generated force (F^{PEE}) when its length exceeded L_0^{CE} (Eq. 5).

$$F^{PEE} = K^{PEE}(L^{CE} - L_0^{CE})^2 \qquad L^{CE} > L_0^{CE} \tag{5}$$

Muscle activation states, ranging between 0 (inactive) and 1 (fully activated), were computed from EMG, accounting for the electromechanical delay between neural excitation, represented by EMG, and muscle force production (Lloyd and Besier, 2003). Net joint moments (M_j) at joint j were computed as the product of muscle force and moment arm (ma) for each muscle n, summed across all k muscles (k=4 in our model) (Eq. 6).

$$M_j = \sum_{n=1}^{k} F_n^{CE} \times ma(n)_j \tag{6}$$

ma was assumed constant with respect to joint angle. Joint moments were applied during a forward dynamic simulation. Joint kinematics were computed by numerically integrating the equations of motion over 1/120 second time intervals using a 4th order Runge–Kutta method (Chadwick et al., 2009).

2.3. Numerical optimization

Twenty-two musculoskeletal parameters, constrained to approximate physiologic ranges (Holzbaur et al., 2005b), were computed by constrained global numerical optimization. Six parameters were computed for each muscle (Table 1), except, for wrist flexor and extensor muscles that only crossed the wrist and had no moment arm at the MCP joint,ma_{MCP} was set to zero. These parameters were chosen because they strongly influence the force- and moment-generating behavior of muscle.

For each subject, data from 5 of the 10 trials, one selected arbitrarily from each of the five movement types, were used for optimization. In each optimization loop, muscle activations were control inputs during a forward dynamic simulation. Since the range of motion of the wrist is greater than that of the MCP joint (Norkin and White, 2009), musculoskeletal parameters were optimized in order to minimize the

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