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A comparison of static and dynamic optimization muscle force predictions during wheelchair propulsion

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ABSTRACT

The primary purpose of this study was to compare static and dynamic optimization muscle force and work predictions during the push phase of wheelchair propulsion. A secondary purpose was to compare the differences in predicted shoulder and elbow kinetics and kinematics and handrim forces. The forward dynamics simulation minimized differences between simulated and experimental data (obtained from 10 manual wheelchair users) and muscle co-contraction. For direct comparison between models, the shoulder and elbow muscle moment arms and net joint moments from the dynamic optimization were used as inputs into the static optimization routine. RMS errors between model predictions were calculated to quantify model agreement. There was a wide range of individual muscle force agreement that spanned from poor (26.4% F_{max} error in the middle deltoid) to good (6.4% F_{max} error in the anterior deltoid) in the prime movers of the shoulder. The predicted muscle forces from the static optimization were sufficient to create the appropriate motion and joint moments at the shoulder for the push phase of wheelchair propulsion, but showed deviations in the elbow moment, pronation–supination motion and hand rim forces. These results suggest the static approach does not produce results similar enough to be a replacement for forward dynamics simulations, and care should be taken in choosing the appropriate method for a specific task and set of constraints. Dynamic optimization modeling approaches may be required for motions that are greatly influenced by muscle activation dynamics or that require significant co-contraction.

1. Introduction

Numerous studies using inverse dynamics analyses have documented high mechanical loads on the upper extremity (UE) during handrim wheelchair propulsion (Rodgers et al., 1994; Robertson et al., 1996; Boninger et al., 1997; Kulig et al., 1998; Boninger et al., 1999; Boninger et al., 2000; Boninger et al., 2002; Veeger et al., 2002a, b; Rozendaal and Veeger, 2003). While providing useful data and insights that can aid in determining potential links between propulsion mechanics and the development of pain, clinical interpretations made from intersegmental joint forces and moments calculated from an inverse dynamics model are limited. Intersegmental forces do not represent the articulating surface load (i.e., joint contact force), and moments are an estimate of the net action of all muscles crossing each joint. Because measuring in-vivo joint contact forces without an invasive procedure is not feasible, more complex musculoskeletal modeling and optimization techniques are needed to estimate joint contact forces and individual muscle contributions to the joint moment. This information is useful in identifying activities and conditions that place manual wheelchair users at increased risk for shoulder pain and rotator cuff injury.

The majority of prior investigations have utilized static optimization techniques to solve the indeterminate muscle force distribution problem at the shoulder joint during wheelchair propulsion (Veeger et al., 2002a, b; Lin et al., 2004; van Drongelen et al., 2005; van Drongelen et al., 2006; Dubowsky et al., 2008; Morrow et al., 2009; Rankin et al., 2011). Dynamic optimization techniques, which have been found to be useful in other movements such as pedaling, standing and walking (Rankin and Neptune, 2010; Nataraj et al., 2012; Miller et al., 2013) have recently been used with upper extremity models to investigate manual wheelchair propulsion biomechanics (Rankin et al., 2011; Rankin et al., 2012; Slowik and Neptune, 2013). Compared to dynamic optimization, static optimization has a much lower computational cost. However, unlike dynamic optimization, the method is time-independent and does not include the time-dependent physiological nature of muscles. Thus, it is not clear whether static optimization predictions of

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muscle forces can be used to investigate wheelchair propulsion mechanics. Anderson and Pandy (2001) investigated the necessity of complex forward dynamics techniques to simulate half a gait cycle during walking using a lower extremity (LE) model and found the muscle force predictions between static and dynamic approaches were practically equivalent. However, it is unknown if Anderson and Pandy's (2001) conclusions are generalizable to UE tasks. A comparison performed for the UE may differ from the LE due to its increased range of motion, complexity of the musculature and different task demands.

Therefore, the primary purpose of this study was to assess whether the UE muscle force and muscle work predictions during the push phase of wheelchair propulsion generated from static and dynamic optimization are the same. A secondary purpose was to compare the differences in predicted shoulder and elbow kinetics and kinematics and handrim forces between a dynamic simulation and a dynamic simulation driven by the statically-optimized muscle forces. We expected that, despite the increase in complexity and range of motion of the movement compared to walking, static and dynamic muscle force predictions would show good agreement. However, due to the complex non-linear UE dynamics, we expected that even small differences in the static muscle force solution would cause the simulation to deviate from the forward dynamics solution when used to drive the model.

2. Methods

2.1. Data collection

A previously collected dataset using a cross-sectional, observational study design of manual wheelchair users (Rankin et al., 2012) was used as the basis for performing the static and dynamic optimization analyses. Twelve experienced manual wheelchair users (10 men, 2 women) with an average age of 32 years provided informed consent. All data collection procedures were performed at MAX Mobility, LLC (Antioch, TN). Testing was conducted on a custom-built wheelchair treadmill while each subject propelled their own wheelchair at a self-selected speed (Rankin et al., 2012). Shoulder and elbow kinematics were obtained using a 3-camera motion capture system (Phoenix Technologies Inc., BC, Canada) with an active marker set. Markers were placed on the head, sternum and right side acromium process, lateral epicondyle, radial and ulnar styloids, 3rd and 5th metcapophalangeal joints, 2nd proximal interphalangeal joint and wheelchair hub. Marker data were collected at 100 Hz and low-pass filtered (10 Hz) using an eighth-order Butterworth filter. Handrim kinetics and wheel angle were recorded at 200 Hz using an OptiPush force sensing wheel (MAX Mobility, LLC) (Richter and Axelson, 2005) and low-pass filtered (20 Hz) using an eighth-order Butterworth filter.

2.2. Musculoskeletal model

An UE musculoskeletal model was developed in SIMM (Musculographics, Inc., Santa Rosa, CA) with associated muscle properties and origin/insertion sites based on the work by Holzbaur et al. (2005) and Rankin et al. (2011). The model consisted of rigid segments representing the trunk, right upper arm, forearm (independent ulna and radius) and hand of a 50th percentile male. Articulations were defined between rigid segments to represent anatomical joints at the shoulder (3 DOF: shoulder elevation plane, shoulder elevation angle, shoulder internal/external rotation) and elbow (2 DOF: Flexion–Extension, Pronation–Supination). Trunk lean and hand location were constrained based on experimental data and a scapulo-humeral rhythm was defined from cadaver data of subjects with no apparent upper extremity dysfunction (de Groot and Brand, 2001). The model was driven by 26 Hill-type musculotendon actuators to represent the major UE muscles crossing the shoulder and elbow joints. Each actuator was defined using two states (activation, fiber length) and was governed by intrinsic force–length–velocity relationships (Zajac, 1989). All other model parameters were selected from Holzbaur et al. (2005). Musculotendon lengths and moment arms were determined as a function of the joint angles at each time step of the motion using polynomial equations (Rankin and Neptune, 2012). The resultant dynamic model had 8 kinematic states (trunk lean, three shoulder angles, elbow flexion–extension and pronation–supination) and 26 muscle activation and fiber length states.

2.3. Dynamic and static optimization

Dynamic simulation data were obtained from the push phase of a single forward dynamics simulation that reproduced the group average experimental data (identical to Rankin et al., 2011) using a global optimization algorithm (simulated annealing, Goffe et al., 1994). The algorithm determined the muscle excitation patterns that minimized differences between simulated and experimental joint kinematics (shoulder, elbow and wrist) and handrim forces using an optimal tracking cost function in the form of Neptune et al. (2001):

$$J = \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{(Y_{ij} - \widehat{Y}_{ij})^2}{SD_j^2}$$

where Y_{ij} and $\widehat{Y}_{ij}$ are the experimental and corresponding simulation value for variable j at time step i and SD_j is the standard deviation of variable j calculated from the experimental data. Based on the assumption that the efficiency of the human neuromuscular system is governed by the minimization of redundant muscle activation for a given task, an additional term was included in the cost function that was directly proportional to muscle stress (i.e., force ratio, expressed as percentage of maximum isometric force) to reduce co-contraction. The average force percentage was calculated over the motion for each muscle and then summed across all muscles. Individual terms in the tracking cost function were weighted independently and adjusted in an iterative manner until tracking of joint kinematics and handrim kinetics were within 1SD of the experimental data (Figs. 1 and 2). The weight on the muscle stress term was then increased iteratively until an increase in tracking errors was observed.

To allow for a direct comparison between approaches, the muscle moment arms and net joint moments at the shoulder and elbow from the dynamic optimization were then used as input into the static optimization routine (Morrow et al., 2009). For the static optimization, the identical musculoskeletal

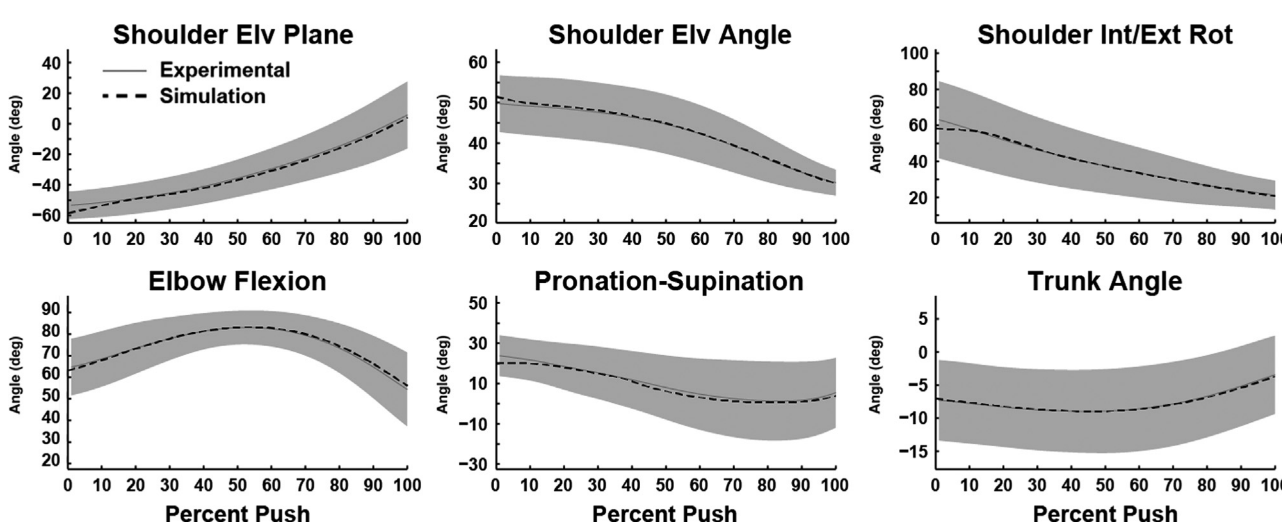

Fig. 1. Comparisons between the experimental and dynamic simulation kinematic data. Average experimental and simulation values are represented by solid and dashed lines, respectively. Shaded regions represent ±1SD of the experimental data.