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DEVELOPMENT OF AN EMG OPTIMIZATION FRAMEWORK FOR USE IN A COMPLEX OPENSIM LOWER BACK MUSCULOSKELETAL MODEL

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INTRODUCTION

The requirements of everyday life place mechanical demands upon the joints of the body. Some of these loads are beneficial, while others may be deleterious. For example, walking is often prescribed for aerobic and musculoskeletal conditioning of the lower back [1]. In contrast, certain arduous lifting and asymmetric tasks may contribute to the high worldwide incidence of lower back pain [2,3]. Without ethical methods to directly quantify *in vivo* demands, it is difficult to classify many tasks of daily life as beneficial or not. *In silico* musculoskeletal models of the lower back can overcome these ethical concerns and allow us to better understand *in vivo* demands during a variety of tasks [4].

Like all joints in the human body, the lower back has many more available controls (muscles) than it does degrees of freedom (DoF). This results in an indeterminate system with an infinite combination of potential muscle forces to accomplish a given movement. Biomechanists traditionally apply various optimization approaches to establish a feasible solution to predict muscle and joint loads [4]. Though these solutions will satisfy the constraints of the system, it is unlikely that the central nervous system (CNS) minimizes a universal objective function for all tasks. Further, most generic optimization approaches (e.g. the minimization of muscle activations [5]), often underpredict antagonist co-activations, a significant concern in back models. To overcome these limitations, Cholewicki and McGill [6] introduced a hybrid approach (EMGopt) which incorporates participant-specific electromyography (EMG) responses to better individualize the calculated joint demands while satisfying the equations of motion.

The aim of the present study is to develop the framework for an EMGopt-driven solution using a complex OpenSim model of the lower back [7], and to test its efficacy. To this end, we compared L5/S1 compression loading results from our EMGopt solution to a traditional static optimization (SO) algorithm across select sub-maximal tasks.

METHODS

All experimental data were collected from a fit and healthy female participant (38 years; 60.5 kgs; 1.7m). After providing informed consent, she performed a series of maximal voluntary contractions (MVC) of the trunk musculature [8], followed by five sub-maximal conditions: quiet standing with 0, 4.5, and 9.1 kg weights in each hand, and walking at a comfortable self-selected speed (1.3 m/s) with and without an artificial 19 mm leg length asymmetry invoked by an EvenUp™ Shoe Leveler placed on her right foot.

Full-body kinematics were captured at 100Hz with 60 reflective markers and 8 high-resolution cameras (Qualisys AB, Sweden). Muscle EMG signals were detected by 12 surface electrodes (Delsys Inc., USA) positioned [8,9] bilaterally over 6 trunk muscles: 1) rectus abdominis, 2) external obliques, 3) internal obliques, 4) latissimus dorsi, 5) longissimus dorsi, and 6) iliocostalis. Ground reaction force (GRF) and gait pacing were supplied by an instrumented treadmill (Treadmetrix, USA). EMGs and GRFs were collected at 2000Hz. EMGs were post-processed [8] and scaled to peak MVC values. GRFs and processed EMGs were down-sampled to sync with the kinematic data.

Two separate full-body lumbar spine models with 17 segments, six lumbar joints, and 238 musculotendon actuators (MTAs) were defined in OpenSim 4.0 [10], based upon a previously validated model [7]. The two models were used in different phases of the solution process (Fig. 1). Model m47DoF, with 47 DoF was used to accurately determine the MTA moment arms across all six lumbar joints, to solve the SO, and to compute lumbar joint loads. Model m29DoF was identical but with 18 fewer DoF due to coordinate coupler constraints (CCC) on the lumbar and abdominal joints, which were necessary to accurately calculate the states and resultant joint kinetics of each of the lumbar segments relative to total trunk kinematics.

EMGopt was implemented in a custom MATLAB (Mathworks Inc., USA) script that accessed OpenSim libraries [11]. Recorded EMGs were assigned as MTA activations [9] in the m47DoF model along with segment kinematic states to determine the contribution of each MTA to the 18 resultant lumbar joint moments calculated from m29DoF. MTA forces were then optimized with a *fmincon* sequential quadratic programming algorithm according to the objective function [6]:

$$\min \sum_{i=1}^{238} Memg_{i,j}\,(1-g_i)^2$$

where the sum of the root sum squared moment contributions ($Memg_{i,j}$) from each MTA (i = 1 to 238) about each joint (j = 1 to 6) was constrained to be within 0.5% of the resultant joint moments by minimizing adjustments to their originally assigned force output (g_i) [6,9]. Optimized MTA forces from both EMGopt and OpenSim SO [12] were input to the OpenSim Joint Reaction Analysis Tool [12] to calculate each solution's effect on L5/S1 compressive loads.

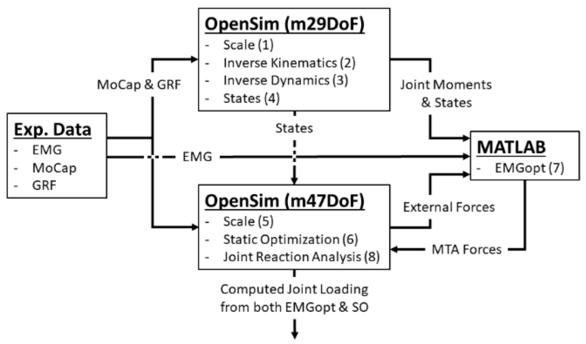

Fig 1: Flow chart of model inputs/outputs processes. Braced numbers depict implementation sequence.

RESULTS AND DISCUSSION

The average L5/S1 compressive loads from the five experimental conditions are shown in Fig. 2. In all conditions, EMGopt predicted larger compressive loads than SO, but both were within reported ranges for lumbar compressive loading [4,13]. The higher EMGopt values are due to the inclusion of more antagonistic MTA forces that are not selected by SO to balance the net joint moments.

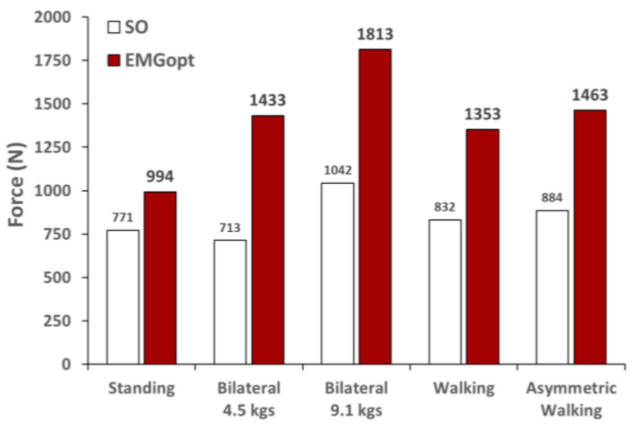

Fig 2: Average L5/S1 compressive loads across the 5 experimental conditions as predicted by static optimization (SO) and hybrid EMG optimization (EMGopt) models.

The three standing conditions are symmetrical about the lumbar joints and produce relatively constant small net joint moments. As anticipated, the EMGopt method predicted increasing L5/S1 compression as the hand-held mass increased, while SO did not predict the same expected pattern. Walking entails larger lumbar moments [14], yet SO predicted only 8% greater lumbar compression than in quiet stance, while EMGopt predicted a larger 36% increase. Asymmetrical gait displayed lumbar loads 6% (SO) and 8% (EMGopt) greater than in normal walking.

Overall, the EMGopt results show greater fidelity to expected lumbar compressive loading than does SO, and reflects how the CNS may respond differently while attempting to brace the lumbar region from different types of external loads [15].

CONCLUSIONS

This study has demonstrated the feasibility of using an EMGopt-driven solution with a complex OpenSim model to examine lumbar compression loading. The EMGopt approach is well suited to distinguish between conditions with similar resultant joint moment demands, but where the CNS muscular response may also be influenced by factors such as antagonist muscle activations or asymmetries. Future model development will include testing on more participants in a larger variety of experimental conditions, and assessment of both compressive and shear loading demands on all lumbar joints. Further, we will investigate the importance of individual vs. group scaling of model joint moment potentials, the influence of how the surface EMG measures are assigned to the 238 MTAs, the importance of high-quality MVCs in minimizing force adjustments (g_i), the shape of the assumed force/EMG relation, and how individual muscles influence joint loading in different tasks. The developed EMGopt model will be used to examine lower back loading in asymmetric gait.

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