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Development of a novel MATLAB-based framework for implementing mechanical joint stability constraints within OpenSim musculoskeletal models

Mohammad H. Akhavanfar [a], Scott C.E. Brandon [b], Stephen H.M. Brown [c], Ryan B. Graham [a,*]

[a] School of Human Kinetics, Faculty of Health Sciences, University of Ottawa, Ottawa K1N 6N5, Ontario, Canada
[b] School of Engineering, College of Engineering & Physical Sciences, University of Guelph, Guelph, Ontario, Canada
[c] Department of Human Health and Nutritional Sciences, College of Biological Science, University of Guelph, Guelph, Ontario, Canada

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ABSTRACT

The Static Optimization (SO) solver in OpenSim estimates muscle activations and forces that only equilibrate applied moments. In this study, SO was enhanced through an open-access MATLAB interface, where calculated muscle activations can additionally satisfy crucial mechanical stability requirements. This Stability-Constrained SO (SCSO) is applicable to many OpenSim models and can potentially produce more biofidelic results than SO alone, especially when antagonistic muscle co-contraction is required to stabilize body joints. This hypothesis was tested using existing models and experimental data in the literature. Muscle activations were calculated by SO and SCSO for a spine model during two series of static trials (i.e. simulation 1 and 2), and also for a lower limb model (supplementary material 2). In simulation 1, symmetric and asymmetric flexion postures were compared, while in simulation 2, various external load heights were compared, where increases in load height did not change the external lumbar flexion moment, but necessitated higher EMG activations. During the tasks in simulation 1, the predicted muscle activations by SCSO demonstrated less average deviation from the EMG data (6.8% −7.5%) compared to those from SO (10.2%). In simulation 2, SO predicts constant muscle activations and forces, while SCSO predicts increases in the average activations of back and abdominal muscles that better match experimental data. Although the SCSO results are sensitive to some parameters (e.g. musculotendon stiffness), when considering the strategy of the central nervous system in distributing muscle forces and in activating antagonistic muscles, the assigned activations by SCSO are more biofidelic than SO.

1. Introduction

Comprehensive knowledge of internal loads acting on the human body, including muscle forces and joint loads, is essential for designing effective injury prevention (Bolsterlee et al., 2013), rehabilitation (Neptune and Kautz, 2000), and surgery programs (Gomes et al., 2013), to name a few applications. Musculoskeletal modelling is a widely used approach to estimate internal mechanical loads because the direct measurement of these loads requires invasive methods as well as complex and costly experiments (e.g. Rohlmann et al., 1994; Wilke et al., 2001).

Satisfying dynamic equilibrium equations is critical in all biomechanical models; however, within high-fidelity models, the equilibrium equations cannot be solved deterministically because the number of unknown muscle forces is greater than the number of equations (Dreischarf et al., 2016). Generally, optimization (OPT), electromyography (EMG), or hybrid approaches are used

Abbreviations: SO, Static Optimization; SCSO, Stability-Constrained Static Optimization; EMG, electromyography; OPT, optimization; API, Application Programming Interface; ID, Inverse Dynamics; MA, Muscle Analysis; PK, Point Kinematics; FLV, force-length-velocity; S, a system's total stability; GS, geometric stability; EW, external work; RA, Rectus Abdominis; EO, External Obliques; IO, Internal Obliques; ES, Erector Spinae; MVC, maximum voluntary contraction; M_{ext}, external moment; H, load height; M, mass; BCK_{EMG}, average EMG activities of back muscles; ABS_{EMG}, average EMG activities of abdominal muscles; BCK_{SO}, average of back muscles' activities estimated by SO; ABS_{SO}, average of abdominal muscles' activities estimated by SO; BCK_{SCSO}, average of back muscles' activities estimated by SCSO; ABS_{SCSO}, average of abdominal muscles' activities estimated by SCSO; RMSE, root mean square errors; r_, ratio; -L, left; -R, right; q, muscle stiffness coefficient; SCSO-q5, when considering q = 5 in the proposed framework; SCSO-q3, when considering q = 3 in the proposed framework.

* Corresponding author.
E-mail address: rgraham@uottawa.ca (R.B. Graham).

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to resolve this redundancy (Dreischarf et al., 2016). Due to issues of using EMG such as recording activity from deep and wide muscles (Staudenmann et al., 2005; Stokes et al., 2003), cross-talk (Farina et al., 2004), and finding proper gains for muscles to satisfy equilibrium equations (Mohammadi et al., 2015), OPT methods remain the most common (Dreischarf et al., 2016).

In a common OPT problem, the solver minimizes or optimizes a cost function for muscle forces (e.g. minimize the sum of activation squared or cubed) subject to the equilibrium equations and minimum/maximum bounds for muscle forces. Failing to assign realistic activations to antagonist muscles is introduced as the primary shortcoming of the common OPT problem (El Ouaaid et al., 2013). To address the primary limitation of the OPT-based models, some mathematics-based techniques, such as considering non-zero lower bounds for muscle activations (Hughes et al., 1995), or taking opposite signs for the weighting factors assigned to the agonist and antagonist muscles in the objective function (Raikova, 1999) have been proposed. However, considering mechanical stability criteria as an additional constraint to the common OPT problem as a physiologic-based technique has been proposed in a few musculoskeletal modelling studies (Granata and Wilson, 2001; Brown and Potvin, 2005; Hajihosseinali et al., 2014; Samadi and Arjmand, 2018).

The common OPT methods are implemented within many musculoskeletal modelling platforms, including OpenSim, which is the most widely used open-source platform in biomechanics (Delp et al., 2007). To estimate muscle forces, for both inverse dynamic and forward dynamic procedures, there are analysis tools in OpenSim. The Static Optimization (SO) tool is designed in OpenSim to calculate muscle forces using an inverse dynamics approach and by solving the common OPT problem (Seth et al., 2011).

Previous OPT-based models that consider stability criteria are: (i) not accessible for all researchers, and/or (ii) designed only for the spine. Hence, incorporating mechanical stability constraints into the default SO solver in OpenSim would be extremely advantageous to many musculoskeletal biomechanics and biomedical engineering researchers. Therefore, the purpose of this study was to design a novel framework for OpenSim using MATLAB to calculate muscle forces that also satisfy given stability requirements. It was hypothesized that the Stability-Constrained Static Optimization (SCSO) framework would assign more accurate activations than SO to all muscles, and in particular to antagonist muscles. To test the hypothesis, existing models and experimental data in the literature were used.

2. Methods

2.1. Framework development

The default OpenSim SO solver minimizes an objective function in the form of $\sum(a_m)^p$ (Crowninshield and Brand, 1981), subject to two constraints (outlined below), where a_m is the activation of the m^{th} muscle and p is a user-defined constant (default p = 2). Our novel MATLAB-based SCSO framework (The Math Works Inc., Natick, MA, USA) was developed to mirror this approach, while implementing one additional stability constraint. For the SCSO framework, the fmincon optimization solver in MATLAB (default settings) was employed to calculate muscle activations and forces subject to all three constraints, whereas the OpenSim Application Programming Interface (API, OpenSim 3.3) was used to gather all the required model information from OpenSim (Fig. 1).

The first constraint in both SO and SCSO maintains dynamic equilibrium between external and internal moments at each joint level for each instant in time such that:

$$[r]_{nm} * [F]_{m1} = [M]_{n1} \quad (1)$$

where [r] is the matrix of muscle moment arms about the model's coordinates, [F] represents unknown muscle forces, [M] is the matrix of net external moments about each coordinate due to gravity and external forces, n is the number of model coordinates, and m is the number of muscles in the model. To compose this constraint for a desired musculoskeletal model, we used the Inverse Dynamics (ID) tool in OpenSim to calculate the [M] and Muscle Analysis (MA) tool to calculate the [r] at each time step.

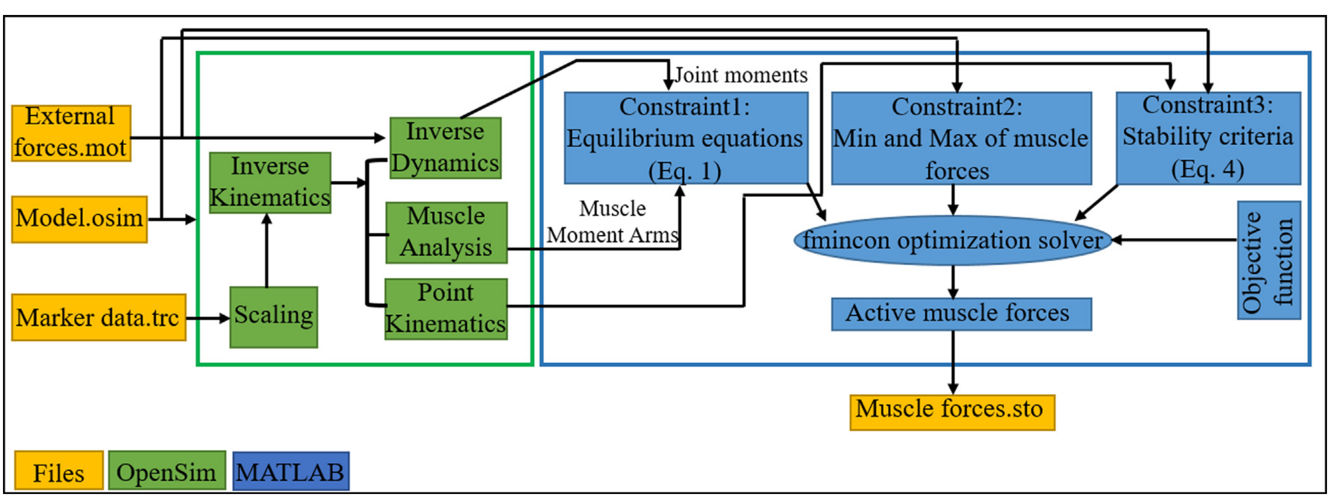

Fig. 1. Schematic of the designed framework. The green and blue boxes show the procedures that are accomplished by OpenSim and MATLAB, respectively. Using the fmincon solver in MATLAB, muscle activations and forces are calculated by solving an optimization (OPT) problem. This OPT problem has a user-defined objective function and three constraints. To form constraints 1, 2, and 3, the user-defined model and external force files, as well as Inverse Dynamics (ID), Muscle Analysis (MA), and Point Kinematics (PK) analysis outputs from OpenSim are required. In addition to the model and external force files, Inverse Kinematics (IK) results are required in OpenSim to run ID, MA, and PK. IK results could be prepared by the user (e.g. the spine modelling in the present study), or by running the IK analysis tool in OpenSim using marker data (e.g. the lower limb model in the supplementary material 2). Users can also scale their musculoskeletal models using the scaling feature provided by OpenSim before running IK. The arrows indicate that a file or outputs of an analysis are used by another part in the framework. MATLAB codes gather the required information from OpenSim either by reading the output files from OpenSim or using the OpenSim Application Programming Interface (API). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

All constraints in an optimization problem should be written as a function of objective function variables (i.e. muscle activations in this framework). Although Eq. (1) is a function of muscle forces, in OpenSim, there are two ways to relate muscle activations to muscle forces:

$$f_i = a_i F_i^0 \tag{2}$$

$$f_i = a_i f(F_i^0, l_i, v_i) \tag{3}$$

where f_i and a_i are the force and activation level of muscle i at a discrete time step, respectively, F_i^0 is a muscle's maximum isometric force, l_i is the muscle length, v_i is the muscle's shortening/lengthening velocity, and $f(F_i^0, l_i, v_i)$ is the muscle's force-length-velocity (FLV) manifold. In our SCSO framework, F_i^0 is determined from the model file, and l_i and v_i are determined from MA results during the movement. Similar to the native OpenSim solver, users can run SCSO with or without considering FLV by matching FLV characteristics to the muscle type used in their model (e.g. Thelen2003Muscle, Millard2012EquilibriumMuscle, etc.).

The second constraint for SO and SCSO states that muscle activations should be between minimum and maximum bounds (0 and 1 is the standard), and the framework pulls these bounds directly from the .osim model file.

The third constraint, found only in SCSO, is the mechanical stability constraint. A mechanical system can be regarded as stable in a static position when the total potential energy in all joints is at its relative minimum, which means the Hessian matrix of system potential energy with respect to its degrees of freedom should be positive semi-definite (Bergmark, 1989; Cholewicki and McGill, 1996). In the present framework, simplified quasi-static stability equations, describing a system's total stability (S) about individual rotational degrees of freedom in the system, were taken from Potvin and Brown (2005) to quantify the muscular and external work contributions to each joint's stability at each time step. The advantage of these equations is that they can be implemented into any 2D or 3D biomechanical model of a joint, or system of joints (Potvin and Brown, 2005).

The simplified stability (S) equation about each rotational coordinate of a system (supplementary material 1) is a function of three terms: (i) muscle forces ([F]), (ii) Geometric Stability (GS), which consists of parameters related to the muscles' geometry and the muscles' stiffness (q), and (iii) External Work (EW). For a user-defined model, movement, and external force set, the SCSO framework calculates GS and EW terms in all directions by performing Point Kinematics Analysis (PK) and Muscle Analysis (MA) via the OpenSim API. A detailed explanation about the calculation of GS and EW terms, as well as other important practical remarks about the SCSO framework, is provided in the supplementary material 1. The general form of stability constraints composed at each time step is:

$$\begin{bmatrix} [GS_x]_{jm} \\ [GS_y]_{jm} \\ [GS_z]_{jm} \end{bmatrix}_{3j*m} [F]_{m1} - \begin{bmatrix} [EW_x]_{j1} \\ [EW_y]_{j1} \\ [EW_z]_{j1} \end{bmatrix}_{3j*1} \geq [Stability\ \ level]_{3j*1} \tag{4}$$

where j is the number of joints, m is the number of muscles, $[F]_{m1}$ is the matrix of unknown muscle forces, and for each joint, both the GS and EW matrices are resolved about the joint-fixed x, y, and z-axes. Stability level is a user-defined matrix with constant elements that should be equal to or greater than zero (Brown and Potvin, 2005).

In sum, for a given model and task, SCSO solves the traditional SO problem with one additional stability constraint and generates the outputs (i.e. muscle activations and forces) in the form of text (.sto) files. These files can then be used for further analysis (e.g. Joint Reaction analysis) in OpenSim.

2.2. Spine model

Granata and Wilson (2001) modelled the spine as a double inverted pendulum, where 12 springs were attached to their system as 12 equivalent trunk muscles. Their spine model possesses some limitations (e.g. the geometry of back muscles); however, it is a simple example of a musculoskeletal model with multiple joints and multi-articular muscles. Therefore, a similar spine musculoskeletal model was developed in OpenSim in the present study.[1] The presented spine model in OpenSim had two custom joints (i.e. lumbar-pelvis and thorax-lumbar), 6 rotational degrees of freedom, and 12 Millard2012Equilibrium muscles (Millard et al., 2013). The six muscles included bilaterally (i.e. Left – L, and Right – R) were: Rectus Abdominis (RA), External Obliques (EO), Internal Obliques (IO), and three Erector Spinae (ES) muscles. Muscle geometry and maximum isometric forces were similar to those in Granata and Wilson (2001). Furthermore, to directly match their model, the allowable activation levels for the muscles were set between zero and one and FLV was not considered.

2.3. Experimental data from previous research studies

2.3.1. Experiment 1

Granata and Wilson (2001) measured EMG of trunk muscles for five men and five women during a series of static trials to validate their model. The trials included four static symmetrical sagittal flexion tasks (i.e. 0° (upright), 15°, 30°, and 45°), and four asymmetrical flexion tasks (i.e. 10° left twist in combination with the aforementioned flexion angles). These published EMG data, normalized to maximum voluntary contraction (MVC), were used in the present study to test SO vs. SCSO performance during each trunk posture and are referred to as Experimental data 1.

2.3.2. Experiment 2

Granata and Orishimo (2001) measured EMG over four bilateral sets of trunk muscles in 10 males and 10 females during another series of static trials to show the role of muscles in joint stability. In this experiment, the external moment (M_{ext}) was kept constant, once at 13.2 and once at 26.5 Nm, while the load height (H) was changed above the lumbo-sacral (L5-S1) joint between 0 and 80 cm. These EMG data, referred to as Experimental data 2, were used in the present study to illustrate differences between default SO and the proposed SCSO framework in predicting changes in activation when the external moment is held constant, but load height is raised.

2.4. Study simulations

2.4.1. Simulation 1

The four static symmetrical sagittal flexion tasks, as well as the four asymmetric flexion tasks from Experiment 1 were simulated directly and both traditional SO and SCSO were applied.

2.4.2. Simulation 2

For simulation 2, the mass properties of the model were changed to match those in Granata and Orishimo (2001), where the trunk mass was 52 kg with zero sagittal moment arm and 20 cm elevation with respect to the lumbar-pelvic joint (Fig. 2). Then a 4.5 kg and 9 kg mass (M) were applied to the trunk at varying

[1] Will be publicly available on: https://simtk.org/projects/stab-so.

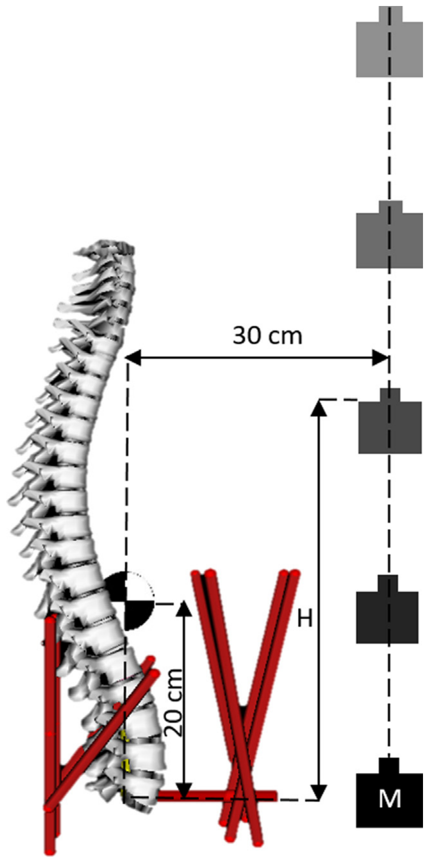

Fig. 2. The developed spine model in OpenSim and a schematic of the simulated tasks in simulation 2. A 4.5 kg and 9 kg mass (M) were applied to the trunk at varying heights (H) from the joint center (i.e. $0 \le H \le 80$ cm, at increments of 20 cm) with a constant sagittal moment arm of 30 cm.

heights from the joint center (i.e. $0 \le H \le 80$ cm, at increments of 20 cm) with a constant sagittal moment arm of 30 cm (Fig. 2).

2.5. Data analysis

2.5.1. Simulation 1 vs. Experiment 1

For simulation 1, the absolute differences between the estimated muscle activations (%MVC) and the mean normalized EMG activations in experiment 1 were computed. Calculated muscle activations by SO and SCSO solvers are not expected to exactly match the measured EMG data because of errors inherent in the musculoskeletal model as well as assumptions in the EMG-to-force transfer function to satisfy equilibrium requirements (Van Dieen and Kingma, 2005). Nevertheless, it was hypothesized that differences between experimental and simulation activations would be smaller for SCSO when compared to the traditional SO.

Due to the symmetric geometry of muscles in the model, both SO and SCSO assign equal activations to the right and left muscles during the symmetrical tasks in simulation 1, and therefore, for these tasks, only muscle activities from one side are reported.

2.5.2. Simulation 2 vs. Experiment 2

Granata and Orishimo (2001) reported average EMG activities (in mV) of back (BCK_{EMG}) and abdominal (ABS_{EMG}) muscles. Thus, in the present study, the calculated muscle activations (% MVC) by SO and SCSO were averaged across back (abdominal) muscles (i.e. BCK_{SO} (ABS_{SO}) and BCK_{SCSO} (ABS_{SCSO}) respectively). Since the EMG data in Granata and Orishimo (2001) were not normalized to MVC, Experimental data 2 were not comparable directly to the predicted muscle activities from SO and SCSO. Thus, both measured and estimated abdominal and back muscle activities at different heights were normalized to the corresponding values at H = 0.

To assess the performance of SO and SCSO algorithms, we compared antagonist activity ratios (r_) between the abdominal and back muscles for EMG, SO, and SCSO results (Eqs. (5)–(7)). Additionally, we computed the root mean square errors (RMSE) of the predicted values (i.e. r_SO and r_SCSO) versus EMG (Eqs. (8) and (9))

$$r\_EMG = ABS_{EMG}/BCK_{EMG} \tag{5}$$

$$r\_SO = ABS_{SO}/BCK_{SO} \tag{6}$$

$$r\_SCSO = ABS_{SCSO}/BCK_{SCO} \tag{7}$$

$$SO_{RMSE} = \sqrt{\frac{\sum_H (r\_SO - r\_EMG)^2}{5}} \tag{8}$$

$$SCSO_{RMSE} = \sqrt{\frac{\sum_H (r\_SCSO - r\_EMG)^2}{5}} \tag{9}$$

2.5.3. Sensitivity analysis

One of the parameters that affects the calculated muscle forces by SCSO is the linear muscle stiffness coefficient (q) (supplementary material 1). A wide range of values (0.5–42) for this user-defined coefficient (q) have been reported (Hajihosseinali et al., 2014). In the present study, for simulation 1 and 2, q was set to five for all muscles, consistent with that in Granata and Wilson (2001) and Granata and Orishimo (2001). However, in simulation 1, another q (i.e. three) in the reported range was also tested to shed light on how the users may adjust SCSO to obtain more biofidelic muscle activation estimates.

2.5.4. Muscle classification

When in all coordinates, a muscle's moment arm's sign was the same as the external moment's sign, it was called an agonist. We called a muscle a complete antagonist when in all coordinates, the muscle's moment arm's sign was opposite to the external moment's sign. When a muscle was neither an agonist nor complete antagonist, it was called semi-antagonist. To better evaluate the predicted muscle activations, the signs of muscle moment arms' values and external moments in the coordinates of the model that have a non-zero external moment were investigated (Table 1).

3. Results

3.1. Simulation 1 vs. Experiment 1 and sensitivity analysis

Using traditional SO, neither RA nor EO (both are back extension antagonists) were activated in the symmetrical (Fig. 3) or asymmetrical (Fig. 4) tasks. These findings were contrary to the previously measured EMG activities of the trunk muscles in experiment 1. However, when considering q = 5 in the proposed framework (SCSO-q5), a non-zero activity of EO in the symmetrical tasks and EO-R in the asymmetrical tasks was estimated. Still, RA was almost silent in all of the symmetrical tasks and in the asymmetric flexion task at 30° and 45°. Comparatively, when considering q = 3 in the framework (SCSO-q3), the framework assigned a non-zero activity to RA and EO in the asymmetrical tasks and RA-R, RA-L, and EO-R in the asymmetrical tasks. These findings were in much closer agreement with the EMG data presented in experiment 1.

Table 1
Signs of external moments and muscle moment arm values. Presented values are for the flexion-extension coordinate and abduction-adduction coordinate of the lumbar-pelvis joint, and the flexion-extension coordinate of thorax-lumbar joint in all tasks of simulation 2 and all symmetrical and asymmetrical tasks of simulation 1. When in all coordinates, a muscle's moment arm's sign is the same as the external moment's sign, it was called agonist. We called a muscle a complete antagonist when in all coordinates, the muscle's moment arms sign was opposite to the external moment's sign. When a muscle is neither an agonist or complete antagonist, it was called semi-antagonist.

Simulation 1-Symmetric tasks and Simulation 2	ES-R	ES-L	RA-R	RA-L	EO-R	EO-L	IO-R	IO-L	External Moment
lumbar-pelvis joint, flexion–extension	+	+	–	–	–	–	+	+	+
thorax-lumbar joint, flexion–extension	+	+	–	–	–	–	–	–	+
Simulation 1-Asymmetric tasks	ES-R	ES-L	RA-R	RA-L	EO-R	EO-L	IO-R	IO-L	External Moment
lumbar-pelvis joint, flexion–extension	+	+	–	–	–	–	+	+	+
lumbar-pelvis joint, abduction–adduction	+	–	+	–	+	–	+	–	+
thorax-lumbar joint, flexion–extension	+	+	–	–	–	–	–	–	+

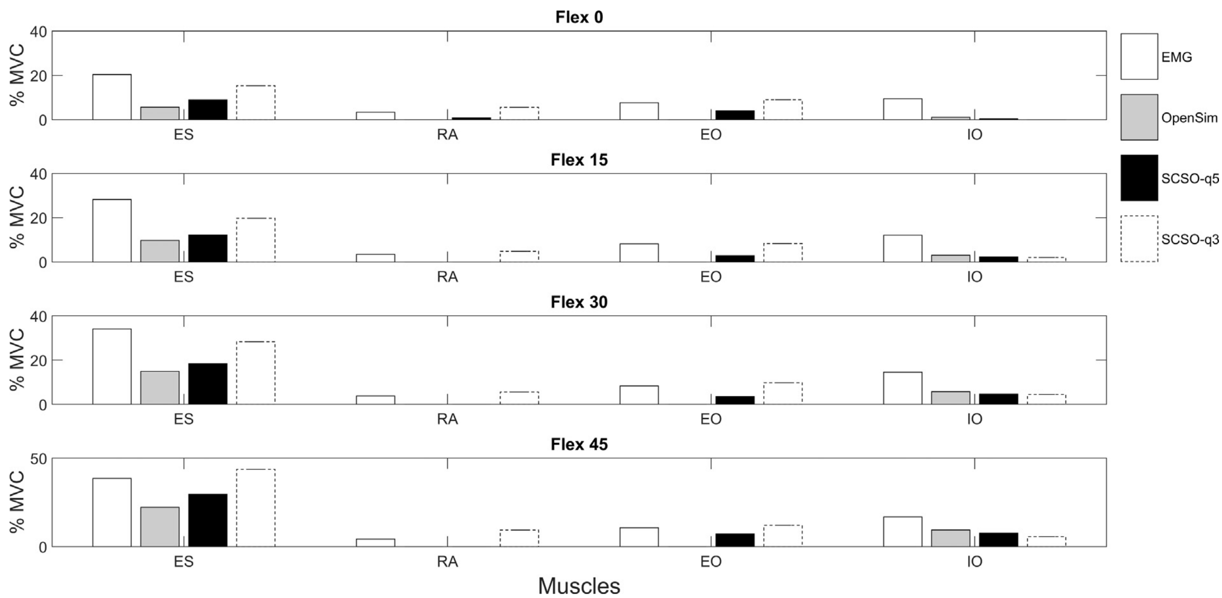

Fig. 3. Simulation 1 results. Muscle activations calculated by the Stability-Constrained Static Optimization (SCSO) framework and the default OpenSim Static Optimization (SO) solver were compared against the average EMG data for 5 men and 5 women reported in Granata and Wilson (2001) during four static symmetrical sagittal flexion tasks. In the framework, q was set to both 5 (SCSO-q5) and 3 (SCSO-q3). Since the estimated right and left muscle activities by SO, SCSO-q5, and SCSO-q3 were equal, the estimated muscle activations in one side were compared to the average of measured EMG activities between right and left muscles. The trunk muscles that were investigated in this study were Rectus Abdominis (RA), External Obliques (EO), Internal Obliques (IO), and Erector Spinae (ES).

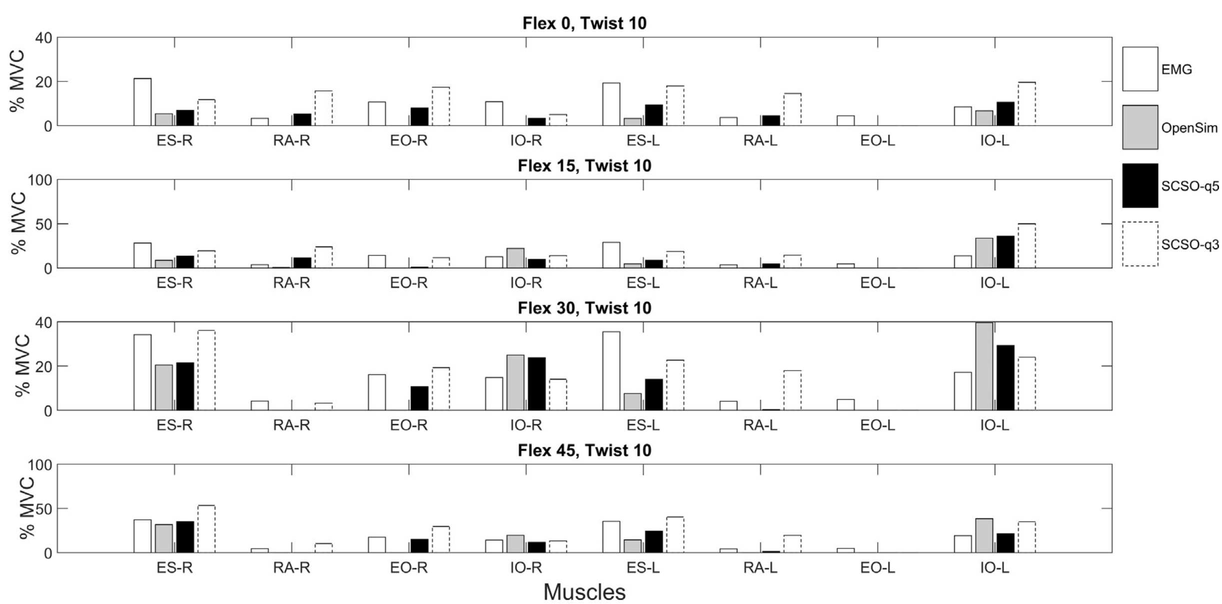

Fig. 4. Simulation 1 results. Muscle activations calculated by the Stability-Constrained Static Optimization (SCSO) framework and the default OpenSim Static Optimization (SO) solver were compared against the average EMG data for 5 men and 5 women reported in Granata and Wilson (2001) during four asymmetric flexion tasks. In the framework, q was set to both 5 (SCSO-q5) and 3 (SCSO-q3). The left (-L) and right (-R) trunk muscles that were investigated in this study were Rectus Abdominis (RA), External Obliques (EO), Internal Obliques (IO), and Erector Spinae (ES).

Table 2
Average percent activation differences between experimental and simulation results. Muscle activations were estimated by the default OpenSim Static Optimization (SO) solver, and the Stability-Constrained SO for both q = 5 (SCSO-q5) and q = 3 (SCSO-q3). The absolute value of the difference between the estimated muscle activations and the measured EMG data were calculated and reported during the symmetrical and asymmetrical tasks in simulation 1. The smallest errors were bolded and italicized in this table. In addition, muscles were categorized into the agonist, semi antagonist, and complete antagonist (Table 1) and the average values for these categories were reported. Furthermore, the average values of the absolute differences across all muscles for SO, SCSO-q5, and SCSO-q3 were calculated and reported.

	Muscles	SO	SCSO-q5	SCSO-q3
Symmetrical Tasks	ES	17.2%	13.0%	***6.1%***
	RA	3.7%	3.5%	***2.6%***
	EO	8.7%	4.3%	***1.1%***
	IO	***8.4%***	9.5%	10.2%
Asymmetrical Tasks	ES-R	13.6%	10.9%	***9.1%***
	RA-R	***3.8%***	4.6%	9.8%
	EO-R	14.6%	***5.9%***	6.1%
	IO-R	9.0%	5.4%	***2.2%***
	ES-L	22.3%	15.7%	***7.3%***
	RA-L	3.9%	***2.1%***	12.7%
	EO-L	4.8%	4.8%	4.8%
	IO-L	15.8%	***9.7%***	17.4%
All Tasks	Agonist	16.0%	12.3%	***7.1%***
	Complete Antagonist	5.6%	***3.8%***	4.1%
	Semi Antagonist	11.8%	***8.6%***	9%
Average	All Muscles	10.2%	7.5%	***6.8%***

In general, the average difference from measured EMG data was smallest for SCSO-q3 versus SCSO-q5 and SO simulation results (Table 2). Across all muscles, the average difference during all tasks was 10.2%, 7.5%, and 6.8%, for SO, SCSO-q5, and SCSO-q3 respectively, and thereby, SCSO-q3 produced results that were the most representative of the EMG data.

3.2. Simulation 2 vs. Experiment 2

When the load height was increased from 0 to 80 cm, the traditional SO predicted zero muscle activations of RA and EO, and constant muscle activations of all muscles, while the normalized ABS_{SCSO} and BCK_{SCSO} increased linearly (Fig. 5). Thus, the SCSO framework's results corroborate experiment 2 where BCK_{EMG} and ABS_{EMG} increased significantly ($p < 0.05$) when the load height increased (Granata and Orishimo, 2001). SO_{RMSE} was 0.3 and 0.26 when holding 4.5 and 9 kg respectively, whereas SCSO was more accurate with $SCSO_{RMSE}$ of 0.03 for both loads (Fig. 6).

4. Discussion

Muscle activations, in addition to maintaining dynamic equilibrium, play a significant role in joint stability, particularly within joints of the spine (Samadi and Arjmand, 2018), knee (Baratta et al., 1988), and shoulder (Labriola et al., 2005). The current SO solver in OpenSim considers limits on muscle forces and the equilibrium demands, yet does not consider stability requirements. Thus, this study aimed to develop a SCSO framework that is generalizable to many OpenSim models. As a proof of this concept, we tested the traditional SO and the new developed SCSO framework for a spine model in this main paper, as well as a lower limb model (Supplementary Material 2).

4.1. Analysis of results

By attempting to minimize the sum of muscle activations squared, the traditional SO assigns zero activations to complete antagonist muscles in the present study. For instance, in simulation 1, RA-L activation in all asymmetrical tasks, and in simulation 2, RA and EO activations were predicted zero by SO, which is contrary to the experimental data. However, the semi-antagonistic muscles may or may not be activated by SO, which depends on all parameters in the OPT problem, such as muscle moment arms (Herzog and Binding, 1992). For example, IO was activated in simulation 2 by SO, while EO-R in the asymmetrical tasks in simulation 1 was not activated, in disagreement with the experimental data.

The zero calculated activations of antagonistic muscles are not the only issue with traditional SO. In simulation 2, since none of

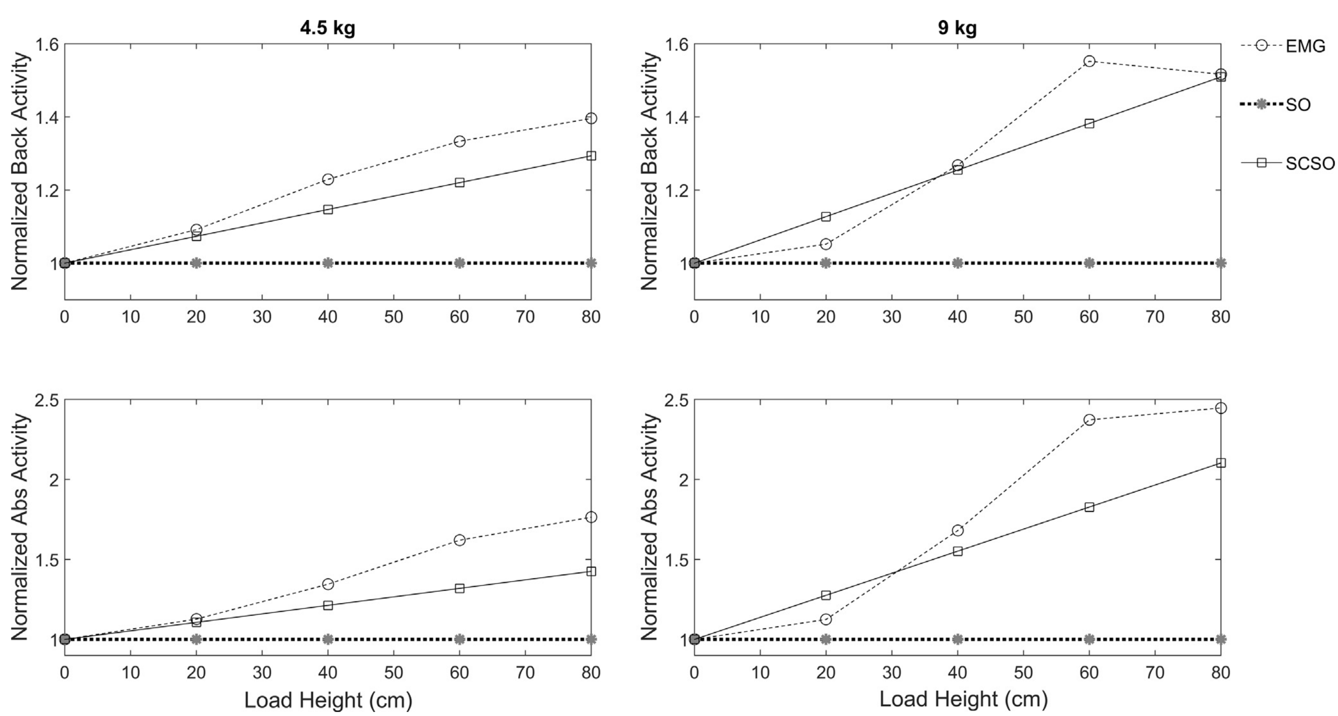

Fig. 5. Simulation 2 results. During the series of static trials in simulation 2 (Fig. 2), the measured and calculated average activities of back and abdominal muscles at each load height were normalized to the corresponding values at H = 0.

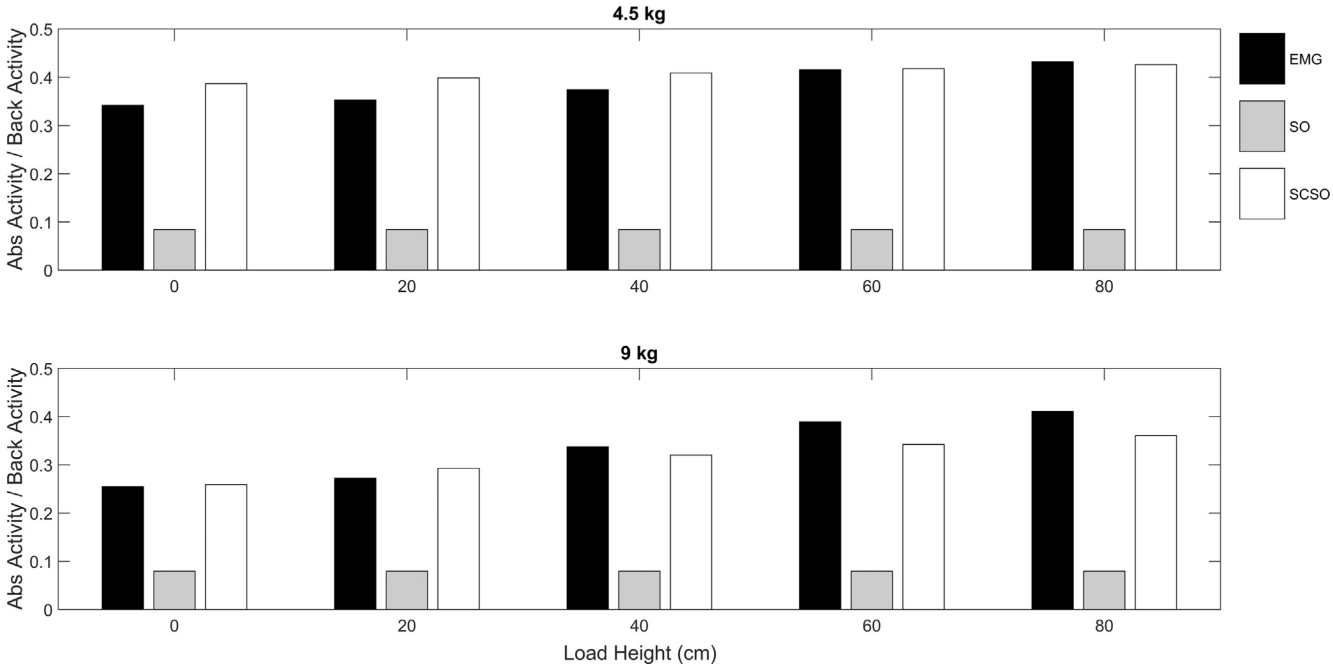

Fig. 6. Simulation 2 results. During the series of static trials in simulation 2 (Fig. 2), at each loading condition (i.e. 4.5 and 9 kg) and each load height, the ratios (Eqs. (5)–(7)) between the average of abdominal and back muscles activations were compared.

the known input parameters (e.g. muscle moment arms or external moment) for the common OPT problem have changed, SO predicts constant muscle activations and forces at different load heights (Figs. 5 and 6), contrary to experimental data.

By considering the stability demands in addition to the equilibrium requirements, the calculated muscle activations by SCSO corroborated better with the experimental data. To maintain stability at each instant in time, SCSO requires that the muscles store a greater amount of potential (elastic) energy than the external work. In simulation 2, the external work (EW) term in Eq. (4) increases in proportion with the load height (supplementary material 1). Therefore, to achieve the stability and equilibrium simultaneously, the predicted activations for both back and abdominal muscles by SCSO should increase, in agreement with the experimental data.

4.2. SCSO limitations

Addition of stability constraints in the SCSO framework increases computational cost versus traditional SO. In the present implementation, SCSO was approximately 4-5x slower than SO (supplementary material 3). However, the majority of this cost comes from read-write operations where model states are gathered from text files (muscle moment arms, joint locations in the world frame, etc.). In future implementations, it would be possible to access these variables directly from memory and significantly reduce computational time. Regardless, SCSO is still much faster than alternatives such as dynamic optimization (Anderson and Pandy, 2001) and simpler to implement than EMG-driven approaches (Lloyd and Besier, 2003).

The performance of the SCSO is highly dependent on the assumed linear muscle stiffness coefficient, q. The magnitude of q affects the amount of energy stored within a muscle during elongation (supplementary material 1). If q is large enough (e.g. $q > 13$ in simulations 1 and 2), muscles will always have the potential to store sufficient energy for stability; thus, SCSO will predict the same muscle forces as the traditional SO. This also explains why SCSO-q5 is similar to SO and in contrast with the experimental EMG data, assigning zero activation to RA in most of the tasks in simulation 1.

The current version of the SCSO framework does not consider contributions of ligaments and other soft tissues to joint passive stiffness when composing the stability constraints. In addition, only static mechanical stability was incorporated into the default OpenSim solver, while dynamic stability, in which the role of kinetic energy and the role of time-dependent dynamic neural feedback for the control of stability are considered (Franklin and Granata, 2007; Graham et al., 2012) was neglected. These limitations will be addressed in future add-ons to the SCSO framework.

4.3. Conclusions

In summary, the presented SCSO framework: (i) calculates muscle activations and forces that not only satisfy dynamic equilibrium in body joints but also satisfy crucial static stability requirements, (ii) can produce results (i.e. muscle activations and forces) that corroborate with experimental data better than, or at least as well as, the default OpenSim SO solver, and (iii) could be used freely by many models that have been developed and will be developed through OpenSim.

Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2019.05.007.

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