Muscle co-contraction in upper limb musculoskeletal model: EMG-assisted vs standard load-sharing

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Abstract

Estimation of muscle forces in over-actuated musculoskeletal models involves optimal distributions of net joint moments among muscles by a standard load-sharing scheme (SLS). Given that co-contractions of antagonistic muscles are counterproductive in the net joints moments, SLS might underestimate the co-contractions. Muscle co-contractions play crucial roles in stability of the glenohumeral (GH) joint. The aim of this study was to improve estimations of muscle co-contractions by incorporating electromyography (EMG) data into a shoulder musculoskeletal model. To this end, the model SLS was modified to develop an EMG-assisted load-sharing scheme (EALS). EMG of fifteen muscles were measured during arm flexion and abduction on a healthy subject and fed into the model. EALS was compared to SLS in terms of muscle forces, GH joint reaction force, and a stability ratio defined to quantify the GH joint stability. The results confirmed that EALS estimated higher muscle co-contractions comparing to the SLS (e.g. above 50 N higher forces for both triceps long and biceps long during arm flexion).

Keywords: muscle over-actuations, inverse dynamics, muscle force estimations, antagonistic muscle co-contractions, Hill-type models

1. Introduction

Noninvasive measurement of muscle forces remains an elusive goal [1]. However, estimations of these forces can be obtained using musculoskeletal models.

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In the available musculoskeletal models, equilibrium equations are obtained for net joint moments using inverse dynamics [2–4]. There are more muscles than the number of the equilibrium equations (over-actuation). Therefore, a standard load-sharing scheme (SLS) is used to distribute the net joint moments among muscles [5–7]. The SLS estimates muscle forces by optimizing a physiological cost function subject to constraints. The constraints are associated with the equilibrium equations, muscle forces upper/lower bounds, and joints stability [8]. Antagonistic muscles are counterproductive in the net joint moments. Therefore, SLS might underestimate forces produced by antagonistic muscles (co-contractions) [9–12], consequently underestimating joint reaction forces [13–15]. Estimations of muscle and joint forces could be improved by considering co-contractions [16–18].

For the upper extremity, few studies investigated muscle co-contractions. Co-contractions were enforced either by tailoring the optimization of SLS [8, 19, 20] or by explicit use of measured EMG data [10, 15, 21–23]. Negative weighting factors were introduced to enforce co-contraction by alleviating the SLS cost function growth [19, 20]. The choice of weighting factors required *a priori* knowledge of antagonistic muscles. However, this was not straightforward to achieve, given that muscles could act simultaneously as agonistic and antagonistic. A stability constraint replicating the stabilizing and proprioceptive effects of musculotendinous structures was introduced for the GH joint [2, 3, 8]. It constrained SLS solutions such that the resulting GH joint reaction force (JRF) always pointed toward inside of the glenoid fossa. On the other hand, explicit use of measured EMG data could provide rather straightforward estimations of co-contractions [10, 15, 21–23]. The relationship between EMG data and muscle forces is crucial to ensure reliable EMG-based muscle force estimation. However, the EMG-force relationship was often over-simplified [10, 21–23] deviating from nonlinear dynamical behavior of musculotendon units [24]. Besides, there was no guarantee that the net moments reproduced by EMG-based muscle forces would satisfy the equilibrium equations [10, 21, 22]. Therefore, the estimated co-contractions might lack a physiological correspondence. EMG-based muscle forces could shrink feasible sets of SLS. Therefore, co-contractions could be better estimated, if EMG data were measured for more muscles. EMG data were measured for fourteen muscles [15], but only a subset of the measurements could be used simultaneously, otherwise "the model crashed".

The aim of this study was to improve estimations of muscle co-contractions by incorporating muscle EMG data into a shoulder musculoskeletal model. Three main improvements were considered with respect to the state-of-the-art. First, a validated nonlinear dynamical model was used for the EMG-force relationship. Second, the model SLS was modified to develop an EMG-assisted load-sharing (EALS) guarantying that the EMG-based forces would satisfy the equilibrium equations. Third, EMG data of fifteen muscles were measured on a healthy subject during arm flexion and abduction and simultaneously fed into the EALS. Muscle and joint force estimations by EALS were compared with those of the SLS.

2. Methods

EMG and motion data were measured (Section 2.1). A shoulder and elbow musculoskeletal model was developed (Section 2.2). The measured motions were reconstructed (Section 2.3). A musculotendon model was developed (Section 2.4). The EALS was detailed (Section 2.5). The developed EALS was evaluated and compared to the SLS (Section 2.6).

2.1. Measurements

EMG and motion data were recorded on a healthy male subject (29 year, 186 cm, and 85.5 kg) during forward flexion in the sagittal plane and abduction in the frontal plane, both with 2 kg weight in hand and with a fully extended elbow (Fig 1). Both activities were repeated for ten trials.

EMG signals of fifteen superficial muscles were measured at 1500 Hz sampling frequency using AgCl Kendall surface button EMG electrodes and recorded by a 16 channel Desktop DTS system (Noraxon, Arizona, USA). The muscles were deltoid clavicular/acromial/scapular, trapezius C7/T1/T2-T7, pectoralis major sternal, infraspinatus, teres major, triceps brachii long/lateral, biceps brachii short/long, brachialis, and flexor carpi ulnaris. Maximum EMG values were also recorded by performing maximum voluntary contractions (MVC).

A common approach in the literature [25, 26] was used in order to transform the measured EMG signals to muscle excitations. It consisted of high-pass filtering, rectifying, and consequently low-pass filtering the EMG signals. The resulting EMG signals were normalized for each muscle using the maximum of its associated MVC signal. Means and standard deviations (σ_{EMG}) of the parted signals associating to the ten trials were obtained.

Trajectories of eleven palpable bony landmarks were measured by tracking their associated skin-fixed markers using an 8 camera VICON videogrammetry system (VICON, UK) at 100 Hz sampling frequency. The bony landmarks included incisura jugularis (IJ), processus xiphoideus (PX), 7th cervical vertebra (C7), 8th thoracic vertebra (T8), sternoclavicular (SC), acromioclavicular (AC), angulus acromialis (AA), medial epicondyle (EM), lateral epicondyle (EL), radial styloid (RS), and ulnar styloid (US).

The recorded trajectories were low-passed filtered. Then, means of the parted trajectories corresponding to the ten trials were obtained.

2.2. Upper extremity musculoskeletal model

2.2.1. Kinematic model

A shoulder and elbow musculoskeletal model was developed from MRI scans of the same subject (Fig 2a) [3, 27, 28]. It consisted of six rigid bodies including thorax, clavicle, scapula, humerus, ulna, and radius. It had nine degrees of freedom (DOF) attributing to three ball-and-socket joints associating with sternoclavicular (SC), acromioclavicular (AC), and glenohumeral (GH) joints and two hinge joints for humeroulnar (HU) and radioulnar (RU) joints and two holonomic constraints (Fig 2b). Two constraints namely Φ_{TS} and Φ_{AI} restricted trigonum scapulae (TS) and angulus inferior (AI) respectively on the scapula medial boarder to glide over two ellipsoids approximating the thorax and the underlying soft tissues. The ISB recommendations [29] were followed to define six bone-fixed frames. A generalized coordinate vector ($\boldsymbol{q} = [q_1 \ \dots \ q_{11}]^T$) was considered to define the upper extremity configuration. The forward kinematic map (ξ) was developed to define the inertial coordinate of the j^{th} bony landmark ($\boldsymbol{x}_j$) associated with the generalized coordinates at time t (Appendix A.1).

2.2.2. Dynamic model

Mass and inertial properties were attributed to the bone segments according to [2]. The upper extremity equations of motion were derived using the Lagrange's equations (Appendix A.2).

The origins/insertions, via points, and wrapping objects of 42 muscles spanning the upper extremity joints were defined from the MRI scans, including subclavius, serratus anterior upper/middle/lower, trapezius C1-C6/C7/T1/T2-T7, levator scapulae, rhomboid minor/major T1-T2/major T3-T4, pectoralis minor/major clavicular/major sternal/major ribs, latisimuss dorsi thoracic/lumbar/Iliac, deltoid clavicular/acromial/scapular, supraspinatus, infraspinatus, subscapularis, teres minor/major, coracobrachialis, triceps brachii long/medial/lateral, biceps brachii short/long, brachialis, brachioradialis, supinator, pronator Teres, flexor carpi radialis/ulnaris, and extensor carpi radiali long/radialis bervis/ulnaris [27]. Each muscle group of the model can be represented by up to 20 strings (Fig 3). Three strings per muscle were considered for simulations of this study.

2.3. Multi-segment optimization

The measured motion was reconstructed in terms of the generalized coordinates using multi-segment optimization. Given that GH was not a palpable bony landmark, it was missing from the measurements. Both TS and AI were also missing. Because, TS and AI were masked with thick layers of soft tissues and were not effectively trackable [30]. Therefore, a novel method developed in [28] was applied to estimate GH, TS, and AI trajectories without requiring an additional scapula tracking device. Then, multi-segment optimization was used to define the generalized coordinates ($\boldsymbol{q}_i$) for each frame of the measured motions (i) such that the overall distance between the measured markers ($\boldsymbol{x}_{e_j}$) and their corresponding bony landmarks ($\boldsymbol{x}_{m_j}$) was minimized, while satisfying the forward kinematics map (Eq. 1).

$$
\begin{aligned}
\min_{\boldsymbol{q}_i} . \quad & \textstyle\sum_j (\boldsymbol{x}_{m_{j,i}}(\boldsymbol{q}_i) - \boldsymbol{x}_{e_{j,i}})^T W (\boldsymbol{x}_{m_{j,i}}(\boldsymbol{q}_i) - \boldsymbol{x}_{e_{j,i}}) \\
\text{s.t.} \quad & \Phi_{\text{TS}}(\boldsymbol{q}_i) = 0 \\
& \Phi_{\text{AI}}(\boldsymbol{q}_i) = 0
\end{aligned}
\tag{1}
$$

Where, W is a weighting matrix.

2.4. Musculotendon model

A Hill-type musculotendon model was used to estimate the muscle forces associating to the measured EMG signals. It provided estimations of tendon force ($F_{\mathrm{T}}(t)$) for given muscle excitations ($u(t)$) and muscuoltendon lengths ($l^{\mathrm{MT}}(t)$) (Fig 4) [31]. It consisted of two unidirectional coupled dynamics, namely activation dynamics and contraction dynamics. The activation dynamics associated $u(t)$ to muscle activation ($a(t)$). The contraction dynamics accounted for the force reproductions for a given $a(t)$ and $l^{\mathrm{MT}}(t)$ (Appendix A.3). A novel method developed in [28] was used to solve the contraction dynamics such that the resulting tendon force estimations were devoid of artificial transients. In addition, the musculotendon model was validated by reproducing experimentally measured forces on maximally excited rat Soleus [28].

2.5. EMG-assisted load-sharing (EALS)

The equations of motion (Eq. A.2) provided eleven second order differential equations for the resulting generalized coordinates $\boldsymbol{q}$ obtained from the multi-segment optimization (Eq. 1). There were more unknowns (42 muscles times number of strings per muscle) than the number of equations. Therefore, we casted the following EALS to find an augmented muscle force vector $\tilde{\boldsymbol{f}}_i \equiv [\boldsymbol{f}_i^T \ \lambda_{\mathrm{TS}_i} \ \lambda_{\mathrm{AI}_i}]^T$ for each frame of the measured motions i. As per Appendix A.2, $\boldsymbol{f}_i$ is a vector consisting of the magnitudes of all the muscle forces at i. The λ_{TS} and λ_{AI} are Lagrange multipliers associating to the scapula-thorax constraints.

$$
\begin{aligned}
\min_{\tilde{\boldsymbol{f}}_i} \quad & \tilde{\boldsymbol{f}}_i^T P \tilde{\boldsymbol{f}}_i \\
\text{s.t.} \quad & \frac{d}{dt}\left(\frac{\partial \mathcal{L}}{\partial \dot{\boldsymbol{q}}_i}\right) - \frac{\partial \mathcal{L}}{\partial \boldsymbol{q}_i} = \left[\frac{\partial \Omega}{\partial \dot{\boldsymbol{q}}_i} B \ \ \frac{\Phi_{\mathrm{TS}}}{\partial \boldsymbol{q}_i} \ \ \frac{\Phi_{\mathrm{AI}}}{\partial \boldsymbol{q}_i}\right] \tilde{\boldsymbol{f}}_i \\
& \begin{cases} (1-\epsilon) F_{\mathrm{T}_{k,i}} \leq \tilde{f}_k \leq (1+\epsilon) F_{\mathrm{T}_{k,i}} & k \in D_{\mathrm{EMG}} \\ 0 \leq \tilde{f}_k \leq \tilde{f}_{\max_k} & \text{else} \end{cases} \\
& \boldsymbol{\psi}(\boldsymbol{q}_i, \ \dot{\boldsymbol{q}}_i, \ \ddot{\boldsymbol{q}}_i, \tilde{\boldsymbol{f}}_i) \leq \boldsymbol{0}
\end{aligned}
\tag{2}
$$

Where, P is a diagonal matrix including the inverse squared of muscles physiological cross section areas (PCSA). The numerical values for PCSAs were set according to the same data set as for the musculotendon parameters [32]. The cost function ($\tilde{\boldsymbol{f}}_i^T P \tilde{\boldsymbol{f}}_i$) is the sum of squared muscle stresses. The first set of constraints is the equations of motion (Eq. A.2) whose right-hand side is written in a vectorial form. The second set of constraints is the muscle forces upper/lower bounds. The set D_{EMG} includes muscles with measured EMG signals. If the k^{th} muscle segment belongs to D_{EMG}, its tendon force estimated by the musculotendon model ($F_{\mathrm{T}_{k,i}}$) from the measured EMG is used as its upper/lower bounds. The positive coefficient ϵ defines the portion of $F_{\mathrm{T}_{k,i}}$ that is considered. The smallest ϵ that results in feasible solutions is considered for both activities (0.05 and 0.07 for flexion and abduction, respectively). For muscles without measured EMG signals, 0 and $\tilde{f}_{\max_k} = K \text{ PCSA}_k$ are used as their lower and upper bounds, respectively. The Fick constant K was set to 33.011 Nm^{-2} [33]. The third constraint represents the stability constraint and denoted by $\boldsymbol{\psi}$ [27]. The stability constraint $\boldsymbol{\psi}$ restricted the solution such that the resulting GH joint reaction force always pointed toward inside of an elliptic cone that approximated the glenoid fossa. Mathematically, $\boldsymbol{\psi}$ was defined as the scalar product between the normal vectors of the cone surface at the cone base and the GH joint reaction force (Eq. 3).

$$\boldsymbol{\psi} = N.(\sum_k m_k(\ddot{\boldsymbol{x}}_k - \boldsymbol{g}) - D\boldsymbol{f}) \leq \boldsymbol{0}, \quad k = \{\text{Humerus, Ulna, Radius}\} \tag{3}$$

Where, N is the matrix containing the normal vectors, m_k is the mass, $\ddot{\boldsymbol{x}}$ is the linear acceleration of center of mass, g is the gravitational acceleration, and D is a matrix containing the muscle force direction vectors. We considered 40 normal vectors to adequately discretize the boundaries of the glenoid fossa which resulted in 40 inequality constraints representing the stability constraint.

Equation 2 was solved to define $\tilde{\boldsymbol{f}}$ such that the sum of squared muscle stresses were minimized, while the constraints were satisfied. The resulting $\boldsymbol{q}$ from the multi-segment optimization was fed into the musculoskeletal model to obtain l^{MT} for the full span of the measured motion. The musculotendon dynamics (Eq. A.3 and Eq. A.4) could be then solved upfront for the full span of the measured motion to define F_{T_k}. Having provided F_{T_k}, the net joints moments, and the moment arms with a given resolution, the optimization problem of Eq. 2 was carried out separately for each frame of the measured motion (i). The equivalent SLS corresponds to $D_{\text{EMG}} = \{\}$.

2.6. Results analysis

The two measured activities were simulated using both SLS and EALS (Fig 4).

The stability ratio (SR) was defined for the glenohumeral joint based on the intersection of the JRF and an ellipse approximating the fossa (Eq. 4). It quantified the concentricity of the JRF with respect to the glenoid fossa. It is well-known that co-contractions increase the glenohumeral joint stability by centralizing the JRF within the fossa [17]. Therefore, the SR is linked to the GH joint stability obtained by co-contractions.

$$\text{SR}_i = 1 - \left(\frac{d_{\text{IS}i}}{a_{\text{IS}}}\right)^2 - \left(\frac{d_{\text{PA}i}}{a_{\text{PA}}}\right)^2 \tag{4}$$

Where, a_{PA} and a_{IS} are posterior-anterior and inferior-superior radii of an ellipse that approximates the glenoid fossa. $d_{\text{PA}i}$ and $d_{\text{IS}i}$ are intersections of JRF and the glenoid fossa ellipse in posterior-anterior and inferior-superior directions for the i^{th} of the measured kinematics, respectively. The stability ratio lies within [0 1] with SR = 0 being marginal stability (intersection occurred on boundaries of the glenoid fossa ellipse), and SR=1 being a perfectly centered intersection.

The sensitivities of the resulting muscle forces and JRF with respect to $\pm 1\sigma_{\mathrm{EMG}}$ variations of the normalized EMG signals around EMG means were also defined. To this end, a first order approximation [34] of the sensitivity of Eq. 2 with respect to $u(t)$ was calculated [28].

Muscle forces, GH joint reaction force, and stability ratio were presented for the measured flexion and abduction. The sensitivities of the muscle forces and the JRF were also presented. The results were illustrated along the arm flexion and abduction angles corresponding to the flexion and abduction, respectively. The associated results from the SLS were also presented. For the JRF, the corresponding *in vivo* measurements from [35] were also presented. Due to space limits, the complete set of muscle force estimations were left for the Appendix B and only a subset of them were presented.

3. Results

3.1. Muscle forces

Forward flexion in the sagittal plane: While SLS estimated no force for deltoid clavicular and scapular (except between 60° to 80° flexion), EALS estimated forces (higher than 52 N) for the entire movement (Fig 5a). Deltoid acromial force followed similar patterns in EALS and SLS, but it was 30% higher initially in EALS. Deltoid acromial had the highest sensitivity (around 25%) to variations of the normalized EMG.

The supraspinatus and subscapularis forces were 390% and 90% higher in EALS than SLS, respectively. The infraspinatus and teres minor forces were similar in EALS and SLS (less than 10% difference in their maximums).

EALS estimated more than 50 N force for triceps long and biceps long (Fig Appendix B.1). However, SLS estimated only almost zero forces.

Abduction in the fontal plane: EALS estimated above 55 N force for deltoid clavicular, whereas SLS estimated almost zero force (Fig 5b). Almost 145% higher force estimated by EALS for deltoid acromial in the beginning, although SLS estimation was 60% higher at the end of the motion. Both methods estimated very similar forces for deltoid scapular after 50° abduction (normalized root mean squared error > 0.024 and $p < 0.0001$). Deltoid acromial also had the highest sensitivity to variations of the normalized EMG.

Higher maximum forces estimated by EALS for supraspinatus, infraspinatus, subscapularis, and teres minor comparing to SLS. For instance, the maximum subscapularis force was 22% higher in EALS.

EALS estimated above 90 N and 40 N forces for triceps long and biceps long, respectively (Fig Appendix B.2). However, SLS estimated zero forces.

3.2. JRF

The maximum JRF estimations by EALS were 58% and 46% higher comparing to SLS for both flexion and abduction motions, respectively (Fig 6a and Fig 6b). They were 172% and 167% of body weight (855 N) and occurred at 68° flexion and 98° abduction, respectively. The resulting JRFs had around 22% sensitivity to the variations of the normalized EMG signals.

3.3. SR and intersection foci

The SR was higher for EALS than SLS (more stable GH joint) and reached 0.87 (vs 0.56 for SLS) till the end of flexion (Fig 7a). The maximum SR was 46% less in abduction than in flexion according to EALS (Fig 7b).

4. Discussion

The aim of this study was to improve estimations of muscle co-contractions by simultaneously incorporating EMG data of fifteen muscles into a shoulder musculoskeletal model. To this end, the EALS was developed by modifying the SLS of a shoulder and elbow musculoskeletal model. The EALS was evaluated by comparing its muscles forces, JRF, and SR with those of the equivalent SLS. The developed EALS estimated higher muscle co-contractions comparing to the SLS. The JRF was consequently higher comparing to SLS.

During forward flexion, the higher force estimated for deltoid clavicular by EALS coincided with a higher force from deltoid scapular. This was consistent with the previous findings regarding the antagonistic role of deltoid scapular during arm flexion [36]. Their co-contractions resulted in counterproductive moments around the GH joint. Also, higher forces estimated for triceps long and biceps long as antagonistic muscles. Their antagonistic role for the GH joint movements was reported [37].

During abduction, similar co-contractions as those of flexion were estimated by EALS. Furthermore, pectoralis major sternal and teres major had higher forces in EALS, indicating their higher co-contractions. This co-contraction around the GH joint was consistent with previous studies [38].
Comparison of the EALS and the SLS muscle force estimations also illustrated role exchanges among muscle groups with similar roles. For instance, trapezius and rhomboid muscles could contribute in the scapular upward/downward rotation during flexion. EALS estimated more contributions from rhomboid minor/major T1-T2 and less from trapezius C7/T2-T7. The SLS estimations were contrary. Indeed, the use of subject's EMG data in terms of upper/lower bounds in EALS caused these role exchanges. Therefore, this could illustrate the potential of EALS in replicating inter-individual muscle recruitment patterns.

The JRF of EALS for both flexion and abduction activities lied within measurements from different patients with instrumented prosthesis (IP) [35]. However, SLS in general underestimated the JRF in both activities. The IP measurements were averaged per activity among different patients with IP to draw a quantitative comparison between the JRF of EALS and SLS and the IP measurements. Indeed, more patients with the IP measurements as well as more patients/activities simulated by the model were required for the comparison to be statistically relevant. Nevertheless, for flexion motion, the peak JRF was 3 % higher for EALS and 34 % lower for SLS comparing to the peak JRF of the averaged IP1 and IP3 measurements. For abduction motion, the peak JRF was 12 % higher for EALS and 24 % lower for SLS comparing to the peak JRF of the averaged IP1, IP2, and IP3 measurements. The EALS in general overestimated the JRF for the beginning of motions comparing to the averaged IP measurements (23 % and 69 % higher for flexion and abduction, respectively). The trends of the estimated JRF by EALS were in general consistent with the IP measurements. It is worth noting that the IP measurements as means of validation should be used with cautious. The post-surgery patients with IP had impaired musculotendons, and their motions were also compromised due to pain [39]. Therefore, their GH joint functions were expected to be different from our healthy subject.

The SR illustrated the effects of higher co-contractions of EALS on the GH joint stability. The higher co-contractions acted toward stabilizing the GH joint by centralizing the JRF within the glenoid ellipse. For the beginning of both activities the SR was low, indicating that the GH joint stability constraint was active. This was consistent with the previous studies regarding stability of the GH joint [17, 40]. However, in EALS the SR started increasing at lower flexion and abduction angles.

In addition, the stability constraint could oscillate between active and inactive states even for negligible deviations of JRF direction from the stability cone. This was due to the incorporation of the stability constraint as a hard constraint into EALS. However, a soft constraint formulation could avoid these oscillatory behaviors without compromising the physiological correspondence of the stability constraint [41].

The positive coefficient ϵ was used to define the upper/lower bounds from EMG-based muscle forces in EALS. The choice of ϵ could therefore alter the optimal force estimation by changing the feasible set. Smaller values of ϵ could further shrink the feasible set of the EALS comparing to larger values of ϵ. Consequently, higher co-contractions could be estimated. We considered the smallest ϵ resulting in feasible solutions for both activities. This provided the highest estimations of muscle co-contractions using our model and allowed performing an adequately fare comparison between the force estimations of the two simulated activities. However, a sensitivity analysis could quantify the effects of ϵ on the force estimations.

Number of muscle strings considered for each muscle could also affect the final optimal force estimation by altering the dimension (degrees of freedom) of the EALS. However, small effects were reported for the variations in muscle string numbers [42]. We used three strings per muscle to adequately replicate muscles with large attachment sites.

A major limitation of this study was that only one subject was recorded. More subjects would be required to more thoroughly evaluate the model, specially its performance in replicating inter-individual muscle recruitment patterns. Three patients with instrumented prosthesis were considered to find the best combination of EMG signals during forward flexion and abduction [15]. The second limitation was about the musculotendon parameters. The realism of the reproduced forces could be enhanced if these parameters were personalized to our subject. However, it is not yet straightforward to obtain these parameters. The third limitation was that only two activities were considered. This imposed certain limitations ahead of generalizing our results. Future applications of the model should consider more activities, including activities of daily living (ADL).

In conclusion, we verified the potentials of EALS in better estimating muscle co-contractions in a shoulder and elbow musculoskeletal model comparing to SLS. The EALS estimated co-contractions by incorporating fifteen EMG-based muscle forces obtained from a musculotendon model. The incorporation of the EMG-based muscle forces shrank the feasible set of the EALS and therefore more co-contractions could be estimated comparing to the SLS. The JRF estimations better matched *in vivo* measurements, although EALS tended to overestimate JRF. This conclusion should be confirmed by simulating more patients during more movements including activities of daily living.

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Appendix A. Mathematical representations

Appendix A.1. Forward kinematic map (ξ):

The forward kinematic map (ξ) defined the inertial coordinate of the j^{th} bony landmark ($\boldsymbol{x}_j$) associated with the generalized coordinates at time t.

$$\begin{aligned}
&\xi : C_s \subset R^{11} \mapsto W_s \subset R^3 \\
&\xi(\boldsymbol{q}(t)) = \boldsymbol{x}_j(t), \quad j = \{\text{C7}, \ \ldots, \ \text{RS}\}_{1\times 14} \\
&\Phi_{\text{TS}}(\boldsymbol{q}(t)) = ({}_t\boldsymbol{TS}(t) - {}_t\boldsymbol{e}_0)^T E_{\text{TS}}({}_t\boldsymbol{TS}(t) - {}_t\boldsymbol{e}_0) - 1 = 0 \\
&\Phi_{\text{AI}}(\boldsymbol{q}(t)) \ = ({}_t\boldsymbol{AI}(t) - {}_t\boldsymbol{e}_0)^T E_{\text{AI}}({}_t\boldsymbol{AI}(t) - {}_t\boldsymbol{e}_0) \ - 1 = 0
\end{aligned} \tag{A.1}$$

Where, C_s and W_s are the coordinate space and work space of the model [43]. Two holonomic constraints ($\Phi_{\text{TS}} = 0$ and $\Phi_{\text{TS}} = 0$) replicated the kinematic relationships between the scapula and the thorax (scapulothoracic contact). The left-hand side subscript t specifies that the landmarks are in the thorax (inertial) frame. The ellipsoids center is ${}_t\boldsymbol{e}_0$, and E_{TS} and E_{AI} are the ellipsoids matrices. The use of two separate ellipsoids to replicate the scapulothoracic contact reduced the computational complexity of ξ [27] comparing to the previous models where only one ellipsoid was used [2, 8, 15]. The use of one ellipsoid required computing the projections of the TS and AI onto the ellipsoid.

Appendix A.2. Equations of motion:

The upper extremity equations of motion were derived using the Lagrange's equations (Eq. A.2).

$$\frac{d}{dt}\left(\frac{\partial \mathcal{L}}{\partial \dot{\boldsymbol{q}}}\right) - \frac{\partial \mathcal{L}}{\partial \boldsymbol{q}} = \frac{\partial \Omega}{\partial \dot{\boldsymbol{q}}} M + \lambda_{\text{TS}} \frac{\Phi_{\text{TS}}}{\partial \boldsymbol{q}} + \lambda_{\text{AI}} \frac{\Phi_{\text{AI}}}{\partial \boldsymbol{q}} \tag{A.2}$$

Where, $\mathcal{L}$ is the Lagrangian of the model obtained by adding all the bone segments Lagrangians [27, 44]. The $\frac{\partial \Omega}{\partial \boldsymbol{q}} M$ is the generalized force vector. The Ω is a horizontal matrix including the angular velocities of all the bone segments. The vertical matrix M consists of the muscle resultant moments around each one of the five joints. The λ_{TS} and λ_{AI} are Lagrange multipliers associating to the scapula-thorax constraints. The generalized moment arms of the constraints are obtained by their jacobians ($\frac{\Phi_{\mathrm{TS}}}{\partial \boldsymbol{q}}$ and $\frac{\Phi_{\mathrm{AI}}}{\partial \boldsymbol{q}}$) [45].

The matrix M could be written as $M = B\boldsymbol{f}$, where B is the moment arm matrix, and $\boldsymbol{f}$ is a vector consisting of the magnitudes of all the muscle forces. The B was obtained using its geometric definition based on the obstacle set method [46].

Appendix A.3. Musculotendon model:

The means of normalized EMG signals were used as $u(t)$ for each muscle. The $a(t)$ represented the relative amount of calcium release to troponin in muscle fibers. It was obtained from a first order dynamic as follows [24].

$$\frac{da(t)}{dt} = \frac{u(t) - a(t)}{\tau(a(t), u(t))} \quad , \quad \tau(a(t), u(t)) = \begin{cases} \dfrac{\tau_{\mathrm{act}}}{0.5 + 1.5a(t)} & u(t) \leq a(t) \\ \dfrac{\tau_{\mathrm{dact}}}{0.5 + 1.5a(t)} & u(t) > a(t) \end{cases} \tag{A.3}$$

Where, τ_{act} and τ_{dact} are time constants corresponding to muscle activation and deactivation, respectively. Both $u(t)$ and $a(t)$ lie within [0 1].

The contraction dynamics consisted of three elements replicating the force production of the musculotendon, including a contractile element (CE), a passive elastic element (PE), and an elastic element (EE) [24]. The contraction dynamics were derived from a force equilibrium between the muscle fiber and tendon. The following ordinary differential equation is an implicit form of the contraction dynamics [28].

$$\begin{aligned} F_{\mathrm{O}} \left[a(t) f^{\mathrm{L}}(\tilde{l}^{\mathrm{M}}) f^{\mathrm{V}}(\tfrac{l_{\mathrm{O}}^{\mathrm{M}}}{v_{\mathrm{O}}^{\mathrm{M}}} \dot{\tilde{l}}^{\mathrm{M}}) + f^{\mathrm{P}}(\tilde{l}^{\mathrm{M}}) \right] \sqrt{1 - \left(\tfrac{\sin \alpha_{\mathrm{O}}}{\tilde{l}^{\mathrm{M}}} \right)^2} \\ = F_{\mathrm{O}} f^{\mathrm{T}}\left(\tfrac{l^{\mathrm{MT}} - l_{\mathrm{O}}^{\mathrm{M}} \sqrt{\tilde{l}^{\mathrm{M}2} - \sin \alpha_{\mathrm{O}}{}^2}}{l_{\mathrm{S}}^{\mathrm{T}}}\right) \end{aligned} \tag{A.4}$$

Where, $f^{\mathrm{L}}(.)$, $f^{\mathrm{V}}(.)$, $f^{\mathrm{P}}(.)$, and $f^{\mathrm{T}}(.)$ are normalized functions associating to muscle force-length, muscle force-velocity, muscle passive force, and tendon force-length relationships. The normalized functions were obtained by fitting smooth curves (C^{∞}) to experimental data [28]. The maximum (optimum) muscle fiber force is denoted by F_{O}. The normalized muscle fiber length ($\tilde{l}^{\mathrm{M}}$) is obtained as $\frac{l^{\mathrm{M}}}{l_{\mathrm{O}}^{\mathrm{M}}}$ in which l^{M} and $l_{\mathrm{O}}^{\mathrm{M}}$ are the muscle fiber length and its optimum, respectively. The optimum muscle fiber velocity and the tendon slack length are denoted by $v_{\mathrm{O}}^{\mathrm{M}}$ and $l_{\mathrm{S}}^{\mathrm{T}}$, respectively. The $l_{\mathrm{O}}^{\mathrm{M}}$ and $v_{\mathrm{O}}^{\mathrm{M}}$ correspond to the situations when the muscle force-length and muscle force-velocity relationships are at maximum and zero force, respectively. Also, α_{O} is the pennation angle at $l^{\mathrm{M}}_{\mathrm{O}}$.

Equation A.4 could be solved for $\tilde{l}^{\mathrm{M}}$ to consequently provide the tendon force $F_{\mathrm{T}}(t) = F_{\mathrm{O}} f^{\mathrm{T}}(.)$. To this end, $a(t)$, $l^{\mathrm{MT}}(t)$, the five musculotendon parameters (F_{O}, $l^{\mathrm{M}}_{\mathrm{O}}$, $v^{\mathrm{M}}_{\mathrm{O}}$, $l^{\mathrm{T}}_{\mathrm{S}}$, and α_{O}), and an initial condition $\tilde{l}^{\mathrm{M}}(t_0)$ were required. The $a(t)$ was readily obtained from Eq. A.3. The $l^{\mathrm{MT}}(t)$ was calculated for each muscle using the musculoskeletal model. More specifically, the resulting $\boldsymbol{q}$ from the multi-segment optimization was fed into the model. The model defined the paths and consequently the lengths of musculotendons. We set the five musculotendon parameters according to [32].

Appendix B. Muscles forces

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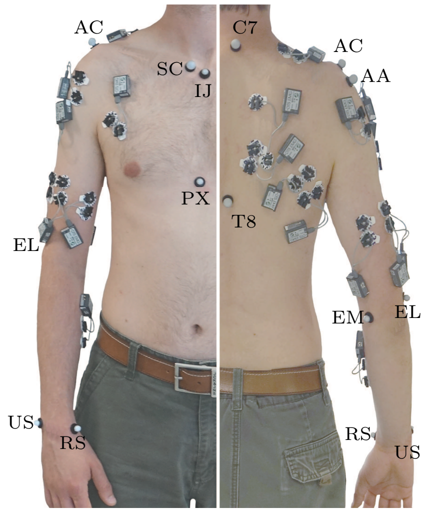
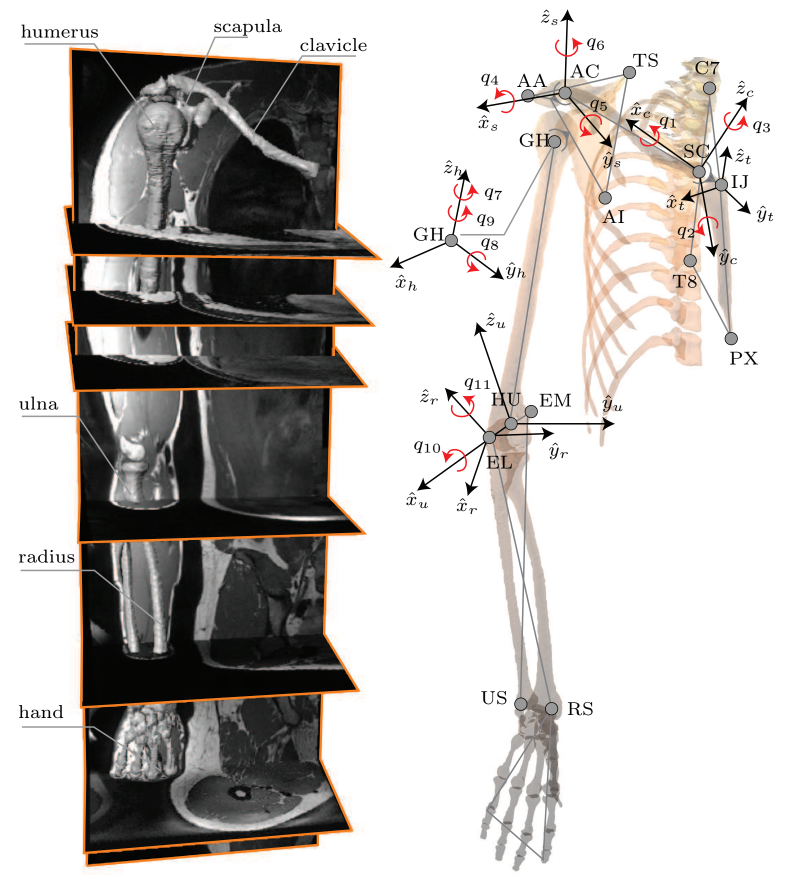


Figure 1: EMG data of fifteen superficial muscles and trajectories of eleven skin-fixed markers were recorded during arm flexion and extension with 2 kg weight in hand.



(a) (b)

Figure 2: (a) MRI scans of a healthy subject were used to develop the model. (b) The kinematic model; fifteen bony landmarks were used, including IJ, PX, C7, T8, SC, AC, AA, TS, AI, GH, EM, EL, and the middle point of EM and EL (HU), RS, and US. The bone-fixed frames were: thorax frame $\{\boldsymbol{IJ}, \hat{x}_t, \hat{y}_t, \hat{z}_t\}$, clavicle frame $\{\boldsymbol{SC}, \hat{x}_c, \hat{y}_c, \hat{z}_c\}$, scapula frame $\{\boldsymbol{AC}, \hat{x}_s, \hat{y}_s, \hat{z}_s\}$, humerus frame $\{\boldsymbol{GH}, \hat{x}_h, \hat{y}_h, \hat{z}_h\}$, ulna frame $\{\boldsymbol{HU}, \hat{x}_u, \hat{y}_u, \hat{z}_u\}$, and radius frame $\{\boldsymbol{EL}, \hat{x}_r, \hat{y}_r, \hat{z}_r\}$. The generalized coordinates consisted of q_1: SC axial rotation, q_2: SC depression/elevation, q_3: SC protraction/retroaction, q_4: AC posterior/anterior tilt, q_5: AC downward/upward rotation, q_6: AC protraction/retroaction, q_7: GH axial rotation, q_8: GH addcution/abduction, q_9: GH flexion/extension, q_{10}: HU extension/flexion, q_{11}: RU pronation/supination. The humerus frame was shifted for better visualizations.

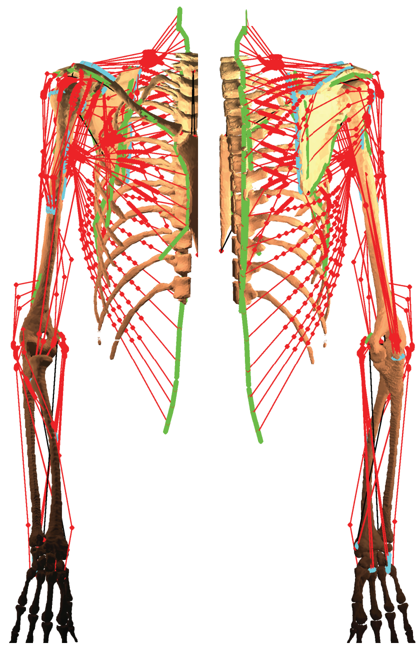


Figure 3: The developed shoulder and elbow musculoskeletal model included 42 muscles that each could be replicated by up to 20 strings (three strings were considred in this illustration).

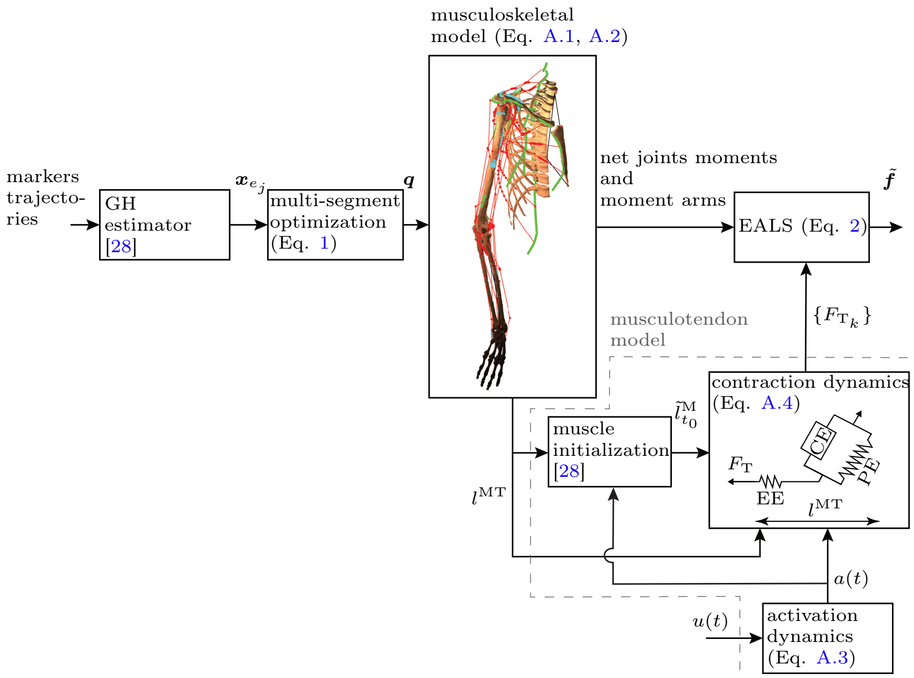
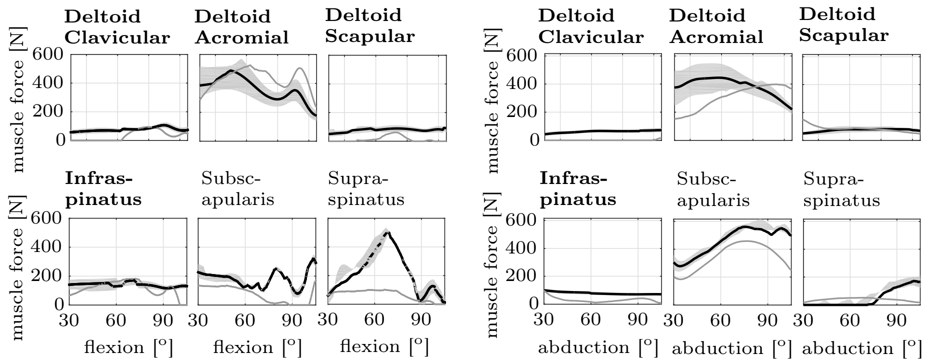
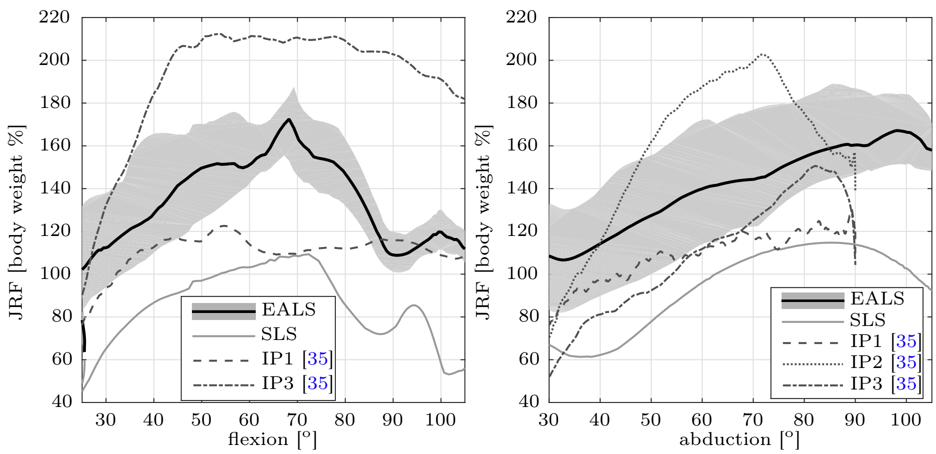


Figure 4: Markers trajectories were fed into the GH estimator. The resulting completed trajectories ($\boldsymbol{x}_{e_j}$) were used in the multi-segment optimization to find $\boldsymbol{q}$. The musculoskeletal model defined the net joints moments, moment arms, and l^{MT}. The muscle initialization provided $\tilde{l}^{\mathrm{M}}_{t_0}$ for the contraction dynamics. The contraction dynamics reproduced the muscle forces associated to muscles with measured EMG ($\{F_{\mathrm{T}_k}\ \forall k \in D_{\mathrm{EMG}}\}$) for given $\tilde{l}^{\mathrm{M}}_{t_0}$, $a(t)$, and l^{MT}. The resulting F_{T_k} were used together with the net joints moments and moment arms in the EALS to estimate $\tilde{\boldsymbol{f}}$.



(a) (b)

Figure 5: Muscle forces estimated by EALS ( ) and SLS ( ) for (a) flexion and (b) abduction with 2 kg weight in hand. The sensitivities to variations of normalized EMG signals were depicted by gray shaded areas. Bold fonts were used to distinguish the muscles with measured EMG data. The muscle force estimations for all the 42 muscles were presented in the Appendix.



(a) (b)

Figure 6: JRF estimated by EALS and SLS for (a) flexion, (b) abduction with 2 kg weight in hand along the corresponding *in vivo* measurements from [35]. The sensitivities to variations of normalized EMG signals were depicted by the gray shaded areas.

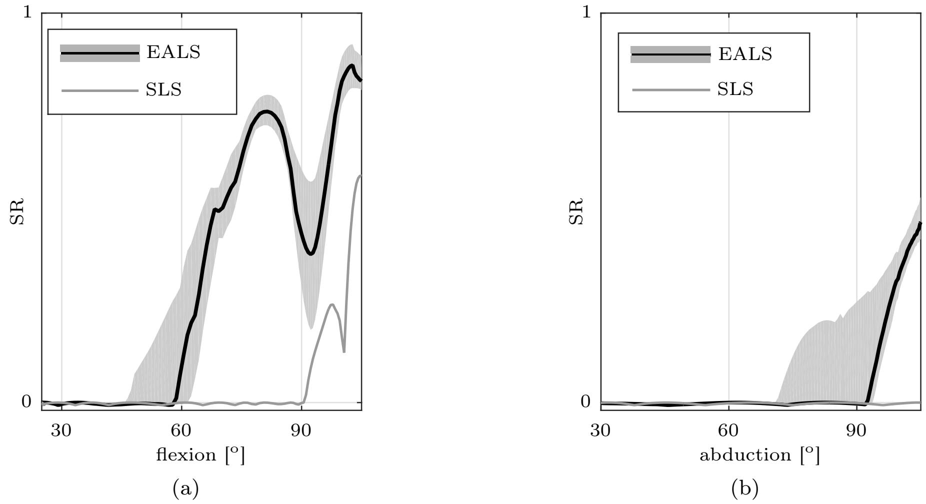


Figure 7: SR from EALS and SLS for (a) flexion and (b) abduction with 2 kg weight in hand. The sensitivities to variations of normalized EMG signals were also depicted by the gray shaded areas.

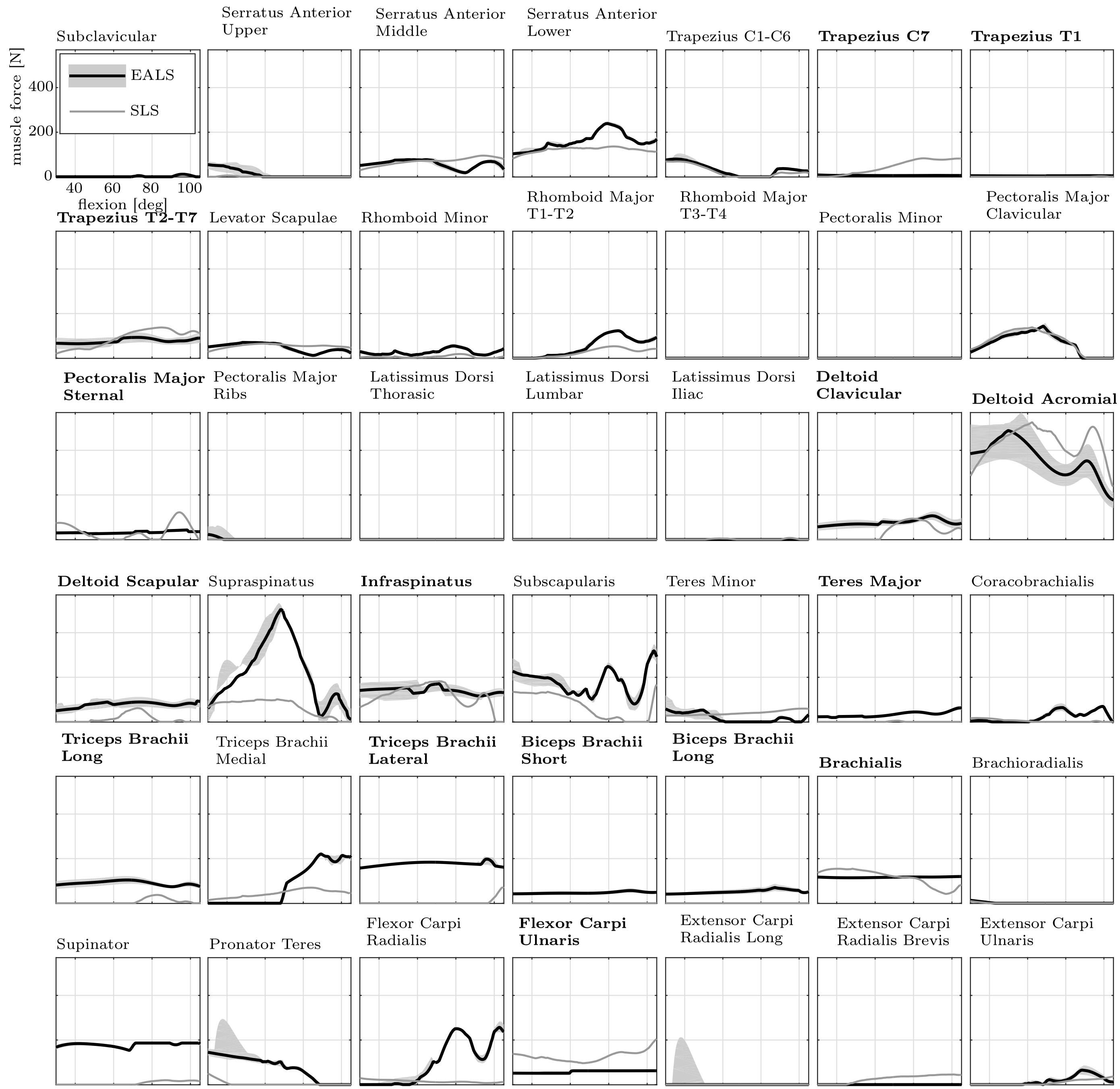


Figure Appendix B.1: Muscle forces estimated by EALS and SLS for flexion. The sensitivities to variations of normalized EMG signals were also depicted by the gray shaded areas. Bold fonts were used to distinguish the muscles with measured EMG data.

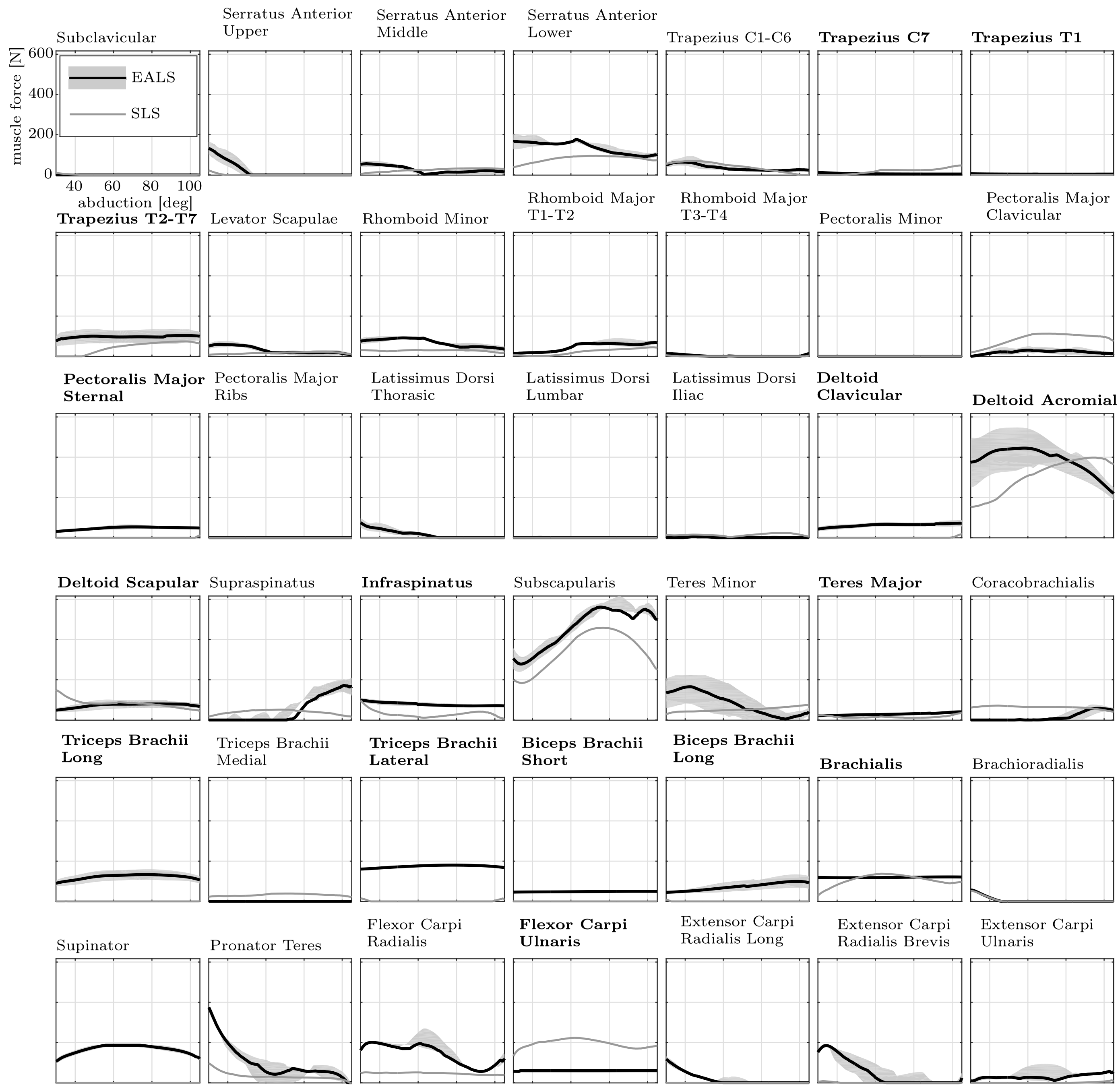


Figure Appendix B.2: Muscle forces estimated by EALS and SLS for abduction. The sensitivities to variations of normalized EMG signals were also depicted by the gray shaded areas. Bold fonts were used to distinguish the muscles with measured EMG data.