Model-based estimation of individual muscle force given an incomplete set of muscle activity measurements

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***Abstract*— Direct *in-vivo* measurement of individual muscle force is limited by the infeasibility of placing force sensing elements in series with musculo-tendon structures using minimally invasive procedures. At the same time, estimating muscle forces using measurements of muscle activity is not always accurate. Even though muscle activity can be measured using non invasive techniques, it is not always available for the complete set of muscles acting around a joint of interest.**

In this paper, we propose a novel estimator that integrates a forward dynamics estimation approach with knowledge of the optimal contraction strategy, obtained using a muscle redundancy solver. With our novel estimator, we are able to obtain accurate estimates of individual muscle forces when measurements of muscle activity are not available for all muscles. We show that the system improves accuracy over standard methods.

I. Introduction

Quantification of individual muscle force applied during tasks that require coordinated muscle co-activation would provide considerable insights on neuromuscular physiology, and enable accurate diagnosis and management of neuromotor disorders. However, direct measurement of individual muscle force is not possible *in-vivo* because of invasive procedures required to place force sensing elements in series to the musculo-tendon units [1]. While multiple estimation approaches of individual muscle force have been presented, it is unclear how accurate they are. Consequently, estimating individual muscle force during complex tasks represents one of the biggest challenges in biomechanics.

Current estimation techniques are largely based on forward dynamics approaches [2], [3], [4]. Such methods require knowledge of the limb's geometry, measurements of joint torques, and measurements of muscle activity, typically obtained using surface electromyography (sEMG). Since sEMG can only measure the activity of superficial muscles, current estimation approaches neglect the contribution of activity from deep muscles to the joint toque. This approximation might be appropriate when estimating forces from the lower limb's muscles [3], however it is likely to results in inaccurate estimates when applied to complex body segments that have many muscles arranged in different layers, such as the forearm muscles that control hand and wrist movements.

In this paper we propose a novel estimator that integrates a forward dynamics estimation approach with knowledge of optimal muscle contraction strategies, obtained using a muscle redundancy solver. We validate our method by comparing our estimator's results against those obtained through existing methods.

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II. Material and Methods

A. Model

Our muscle force estimator is based on a realistic musculoskeletal model adapted from the one previously presented by Saul et. al [5]. The model describes the biomechanics of the wrist joint and includes $m_{tot} = 24$ muscle segments that actuate four degrees of freedom (DOFs) of the upper limb: wrist flexion/extension (FE), wrist radio/ulnar deviation (RUD), pronation/supination, and elbow flexion/extension.

Each muscle segment is modeled as a Hill-type musculotendon unit that assumes the tendon to be inextensible. Given the value of muscle activation a and using the biomechanical parameters proposed in the original model, the musculotendon force f^{MT} of each segment is calculated as

$$f^{MT}(l) = \cos(\alpha(l)) F_{\text{max}}(a\tilde{f}^{A}(l) + \tilde{f}^{P}(l)) \tag{1}$$

where α is the pennation angle, F_{max} is the maximum isometric muscle force, l is the current length of the musculo-tendon unit, $\tilde{f}^{P}$ and $\tilde{f}^{A}$ the passive and active force multipliers, respectively.

A linear dependence is then assumed between the value of a and a quantity M that represents an experimentally obtained measurement of the activity of a single muscle

$$M = \gamma a \tag{2}$$

where γ is the muscle specific proportionality constant.

B. Muscle Force Estimation

Our estimator determines the value of f^{MT} given the limb posture and the value of M. To this goal, the first step is to estimate the set of $\boldsymbol{\gamma}$, then eq. (1) and eq. (2) can be used to obtain the value of f^{MT}.

Since the quantity M is usually not available for all muscles, our method combines a standard forward dynamics estimator with a neural model that estimates the activation of unmeasured muscles based on a cost-function minimization. In this way it is possible to account for the contribution of the unmeasured muscles, thus improving the estimation accuracy. For a generic condition, defined by a set of joint angles and torques, static optimization is used to obtain the optimal set of muscle activations, $\hat{\boldsymbol{a}}_{\boldsymbol{opt}}$, that minimizes the global activation level (GAL), GAL $= \sum a_i^2$. Then, forward dynamics is used to relate the set of measurements obtained from m superficial muscles and the estimated activations $\hat{\boldsymbol{a}}_{\boldsymbol{opt}}$ to estimate the remaining $\bar{m} = m_{tot} - m$ unmeasured muscles contribution to the joint torque $\boldsymbol{\tau}$.

Using eq. (1) we relate muscle force generated by all muscle segments to joint torque

$$\boldsymbol{\tau} = -\mathbf{J^T F} = -\mathbf{J^T} \cos{(\boldsymbol{\alpha})} \mathbf{F_{max}} (\mathbf{\tilde{f}^A a} + \mathbf{\tilde{f}^P}) \tag{3}$$

where $\mathbf{J}$ is the muscular Jacobian whose component r_{ij} represents the moment arm of the muscle i with respect of the joint angle j. $\mathbf{F_{max}}$, $\boldsymbol{\alpha}$, $\mathbf{\tilde{f}^P}$, $\mathbf{\tilde{f}^A}$ are diagonal matrices that contain the respective scalar parameters for each muscle, and $\mathbf{a}$ is a vector that contains the set of all muscle activations.

It is, then, possible to show that, eq. (3) simplifies in:

$$\boldsymbol{\tau} - \tilde{\boldsymbol{\tau}} = -\mathbf{J_m^T} \cos{(\boldsymbol{\alpha})} \mathbf{F_{max}} \mathbf{f^A M} \boldsymbol{\gamma}^{\mathbf{-1}} \tag{4}$$

which is a linear equation of the form $\mathbf{y} = \mathbf{X}\boldsymbol{\beta}$. Where $\mathbf{J_m}$ is a component of $\mathbf{J}$ that contains the moment arms only of the measured muscles and $\bar{\boldsymbol{\tau}}$ is the torque contribution estimated for the unmeasured muscle using the static optimization.

With proper experimental design, it is possible to define a set of n conditions such that the resulting experimental matrix $\bar{\mathbf{X}} = [\mathbf{X_1}; \mathbf{X_2}; ...; \mathbf{X_n}]$ is of full rank. When this condition is satisfied, the vector $\boldsymbol{\beta} = \gamma^{-1}$ is estimated using a standard least squares fit given knowledge of $\bar{\mathbf{y}} := [(\boldsymbol{\tau} - \tilde{\boldsymbol{\tau}})_\mathbf{1}; (\boldsymbol{\tau} - \tilde{\boldsymbol{\tau}})_\mathbf{2}; ...; (\boldsymbol{\tau} - \tilde{\boldsymbol{\tau}})_\mathbf{n}]$.

C. Validation

To validate our estimator, we developed a computational framework that simulates an experimental protocol composed of 20 isometric contractions, applied in five different wrist postures ($[\theta_{FE}, \theta_{RUD}] \in \{[-30, 0], [-15, 0], [0, 0], [15, 0], [30, 0]\}$), under the application of isometric torques in the four cardinal directions including pure wrist FE and wrist RUD torque in both directions, with unitary magnitude. For each configuration, the framework solves the redundancy problem and simulates measurements of muscle activity by assuming values for $\boldsymbol{\gamma} = 10$ for all muscles. Two different sources of physiological and experimental noise are included:

1) selection of a suboptimal contraction strategy $\mathbf{a_{sub}}$ for force generation during a torque-controlled isometric task
2) error in the measurement of individual muscle activity

We assumed the gains of the two sources of error to be randomly selected from uniform distributions, $\epsilon_a \in [0, 0.5]$ and $\epsilon_M \in [-0.2, 0.2]$. Moreover, we assumed that measurements of muscle activity were available only from the five main wrist muscles ECRL, ECRB, ECU, FCR, FCU.

We repeated our virtual experiment $N = 20$ times, and quantified the performance of the estimator in terms of maximum b_{max} and average $\bar{b}$ bias for the values of γ estimated for the five muscles. We compare our method (NMSK) to a standard estimator that does not include information of the optimal control strategy and neglects contributions from all unmeasurable muscles, besides the same restricted set of five muscles (MSKp), as well as when measurements are made available from all muscles (MSKc).

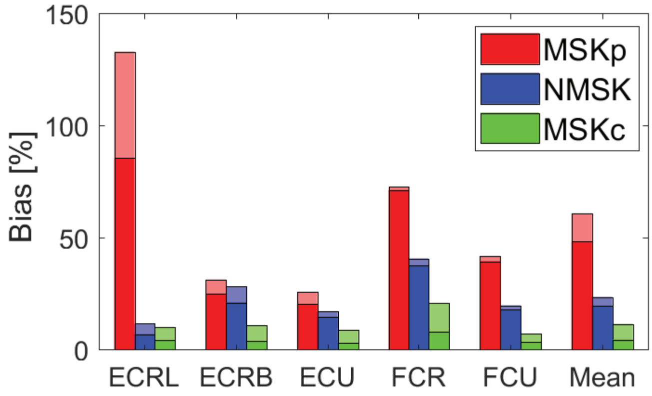

Fig. 1. (Top) Average (solid bars) and max (shaded bars) bias of the estimated γ for the five wrist muscles. In the plot an additional group of bars is added to represent the mean across the different muscles of the relative metrics.

III. Results

The results of the validation analysis are shown in Fig. 1. We show that the proposed method produces an improvement in the estimation of γ for all muscles, in terms of both average ($\bar{b}$) and maximum (b_{max}) bias. Most significantly, the mean across different muscles of $\bar{b}$ decreases from 48% to 19% when using the NMSK estimator (Fig. 1)

IV. Discussion and Conclusion

In this study, we proposed and validated a new estimator that combines a standard forward dynamics estimator with a neural model that estimates the activation of unmeasured muscles based on minimization of a cost-function to obtain individual muscle forces when measurements of muscle activity are not available for all muscles.

The results show that although measuring activity from a partial set of muscles leads to an inevitable bias in estimates of muscle forces for the forearm muscles, the proposed estimation algorithm reduces the average estimator bias of about 30% of the true value.

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