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Preliminary Validation of Upper Limb Musculoskeletal Model using Static Optimization

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Abstract— **Musculoskeletal models are powerful analogues to simulate human motion through kinematic and dynamic analysis. When coupled with feature-rich software, musculoskeletal models form an attractive platform for the integration of machine learning for human motion analysis. Performing realistic simulations using these models provide an avenue to overcome constraints when collecting real-world data sets. This motivates the need to further investigate the validity, efficacy, and accuracy of each available model to ensure that the resultant simulations are transferable to real-world applications. Using the open-source software, OpenSim, the primary aim of this paper is to validate an upper limb musculoskeletal model widely used in research. Muscle activation results from static optimization are evaluated against real-world data. A secondary aim is to investigate the effects of two muscle force generation constraints when evaluating the model's validity. Results show an agreement between the optimized muscle activation trends and real-world sEMG readings. However, it was found that static optimization of the musculoskeletal model is unable to identify voluntary co-contractions since the redundant model has more muscles than the system's degrees of freedom. Thus, future work will look to utilize additional channels of information to incorporate this during analysis.**

I. Introduction

Musculoskeletal models provide an analogue to simulate the kinematics and dynamics borne from the interactions of a series of complex systems in the human body. Historical literature has been used to create most anatomically accurate models. Model parameters are then refined using a variety of anthropomorphic studies [1] and investigations from cadaveric [2] and live human data [3].

The popularity of musculoskeletal models is heavily influenced by the availability of both commercial and open-source software. Notable software which are used during human motion analysis include OpenSim [4], [5], AnyBody [6], and Human Body Model [7]. These are complemented by motion capture systems which can perform three-dimensional kinematic analysis based on captured motions of the markers [8].

Typically, physiological measures are used when assessing simulations and analyses since they are readily accessible and have been characterized extensively in past literature [9]–[11]. Common measures used include electroencephalograph (EEG) [12], galvanic skin response (GSR) [13], and surface electromyography (sEMG) [14]–[16]. However, due to the inherent variability in human anatomy and our physiological responses, demographic models with simple mechanics, such as Fitts' Law [17], have been preferred.

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A recent trend is the integration of machine learning for human motion analysis using physiological measures. This creates opportunities to personalize the learned models for individuals [18], [19], which is a desirable outcome in rehabilitation. However, collecting real-world data sets can be time-consuming, expensive, and cumbersome. Thus, methods that generate realistic simulations can replace or complement real-world data sets in personalized applications. Since sEMG data is commonly used for the integration of machine learning in biomechanics, musculoskeletal models are prime candidates for filling this real-world data gap.

Considering the complexity of human anatomy, there is a need to validate musculoskeletal models to give substance to their simulation data sets. Past works addressing this include performing model comparisons [20] and validations [21], [22]. One challenge when using these models is addressing redundancy from having significantly more muscles than the system's degrees of freedom. The most common method to overcome this problem uses optimization techniques that compare their performance across various constraints [23]–[26]. However, care must be taken when performing validation, verification, and comparison since confounding factors may affect the results ascertained [27].

In this paper, we aim to investigate the validity of an upper limb musculoskeletal model that is widely used in research [28]. We use real-world data to: (1) evaluate and compare muscle activation trends under small loads and gravity, and (2) investigate the effect of different muscle force generation constraints using the model. This paper is organized as follows: Section II outlines the methodology and setup, Section III presents and discusses the results, while Section IV rounds out the paper with conclusions.

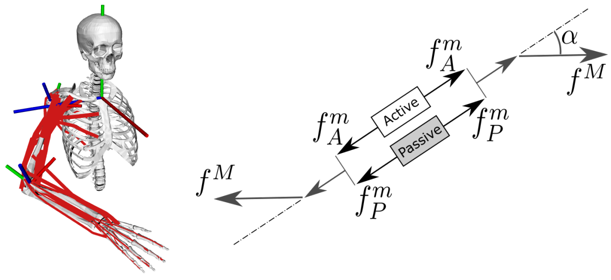
II. Methodology

A. Musculoskeletal Model

The upper extremity model used is modified from an original model with 15 degrees of freedom actuated by 50 Hill-type Muscle Tendon Units (MTU) [28]. The original model was initially validated based on the range of motion and moment arms. Most parameters for the model were set using empirical data from magnetic resonance imaging of live healthy adults [29]. Additional modifications made to the model include:

1) Body mass and inertial properties for the humerus, radius, and capitate were changed based on literature [30] while the remaining body mass and inertial properties were set to 0.

2) The muscles for the model were updated to the more recent *Millard2012EquilibriumMuscle* [31]. Parameters for muscle activation dynamics were kept to the default values. (Activation τ = 0.01, De-activation τ = 0.04, fiber damping = 0.05)



(a) (b)

Fig. 1: (a) The musculoskeletal model used in OpenSim for this study. (b) A typical Hill-type muscle model with force relationships between muscles and tendons.

B. Muscular Architecture

The Hill-type MTU [32] (Figure 1(b)) consists of an active contractile element in parallel with a passive element. An elastic element is placed in series with the force generation mechanism representing the tendons attaching the muscle to the insertion point. The five intrinsic parameters define and normalize the muscle behavior:

- F_0^m - Muscle maximum isometric force
- L_0^m - Muscle optimal length coinciding with F_0^m
- V_0^m - Muscle maximum contractile velocity
- α_0 - Muscle pennation at optimal length
- L_s^t - Tendon slack length.

The active contractile element force is defined as:

$$f_A^m = \tilde{f}_A^m(\tilde{l}^m) \cdot \tilde{f}_V^m(\dot{\tilde{l}}^m) \cdot F_0^m \cdot a, \tag{1}$$

where $\tilde{f}_A^m(.)$ represents the non-linear curve between normalized muscle fiber length and active force, $\tilde{f}_V^m(.)$ represents the curve for normalized muscle fiber velocity against normalized active force, and a is the muscle activation, ranging from 0 to 1 indicating a completely passive muscle through to a muscle with its maximum force output.

The force generated by the passive element is:

$$f_P^m = \tilde{f}_P^m(\tilde{l^m}) \cdot F_0^m, \tag{2}$$

where $\tilde{f}_P^m(.)$ represents the curve for normalized muscle fiber length against normalized passive force.

The total force output of the MTU is then defined by:

$$f^M = (f_A^m + f_P^m)\cos\alpha. \tag{3}$$

C. Validation Setup

One healthy adult male participated in the validation trials conducted for this work. The participant was fitted with six 10mm electrodes (99.9% silver, Delsys, Natick, MA) on muscle groups specified in Table I.

Surface EMG data was recorded (∼1000Hz) using a data acquisition system (LabJack, Lakewood, CO). The sEMG signals were rectified before applying a zero-phase low-pass filter with 3Hz pass and 5Hz stop-band frequencies. A notch filter to cancel out signal noise from power sources were not used based on SENIAM and ISEK recommendations [33].

TABLE I: Sensor placements of the surface EMG electrodes for participants.

Channel	Muscle Group	
1	Biceps Brachii	Short & Long Head
2	Triceps Brachii	Long Head
3		Lateral Head
4	Deltoideus	Medius
5		Posterior
6		Anterior

To capture the kinematics of the participant, four handcrafted motion tracking rigid body assets (each consisting of three retro-reflective markers) were Velcro-mounted, each in relation to the capitate, radius, humerus, and thorax. Three-dimensional marker coordinates were recorded at 125Hz using a 12-camera motion capture system (NaturalPoint, Corvallis, OR). The dynamics of the movements were captured using the reaction forces from a 6-axis force-torque sensor (ATI Industrial Automation, Apex, NC) recording at 125Hz. The participant held the force-torque sensor, allowing for external loads to be inserted at the lunate.

Static optimization to obtain muscular activity was performed using the minimum sum of squared activation as the cost function and, for the sake of efficiency, only every third frame was optimized. We assume this has negligible effect on muscle activation dynamics since voluntary muscle recruitment has been found to be heterogeneous, with torque transmission delays significantly over 25ms [34]. Furthermore, from the inverse dynamic results, coordinates that experience a negligible force ($< 0.1Nm \ or \ 0.1N$) were ignored as a preliminary observation indicate that most are path points for the muscles which are under equilibrium for static optimization. Two sets of analyses were conducted using the same data - one using ideal force generators and the other with force-length-velocity (FLV) constraints [35].

For the validation trials, a series of movements were conducted with the force-torque sensor acting as a small mass. Each movement was repeated by the participant three times in series, including shoulder flexion & extension, shoulder abduction & adduction, horizontal abduction & adduction with internal & external rotations, and water drinking motion.

III. Results and Discussion

The resultant muscle activation trends obtained from static optimization were compared against the six-channel sEMG readings collected during the validation trials. Figure 2 shows the results from the static optimization using the FLV constrained muscle forces for the shoulder flexion and extension motion. The model treats muscle groups as homogeneous entities, despite the heterogeneity of muscle groups in real-world muscle dynamics, thus resulting in the spiking nature of the muscle activation. Taking this into account, the resultant muscle activation across the six different muscle groups show that the whole musculoskeletal model has plausible agreement with real-world trends. The remaining motions exhibit similar trends. Additional figures can be accessed in the repository.

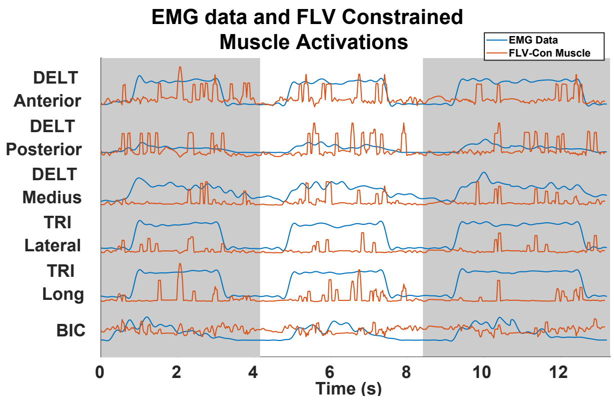


Fig. 2: Results from the preliminary validation trial for shoulder flexion and extension. Static optimization results are based on FLV constrained MTUs and EMG readings are heuristically normalized.

Secondary results for comparisons between ideal force generators, which do not take into account force-length and force-velocity relationship, and FLV-constrained muscles can be observed in Figure 3. We observe that ideal muscles tend to require less activation since the dynamic properties of the MTU typically generate forces lower than the maximum isometric force.

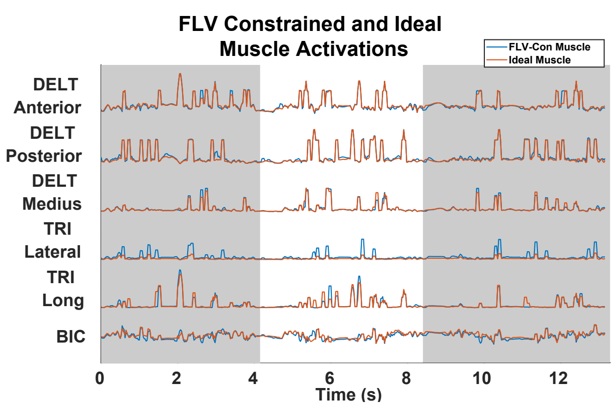


Fig. 3: Results comparing between muscle activation from ideal and FLV constrained force generators.

There are a few factors that may affect the generalization of our findings, especially for different participants. Since we are treating real-world sEMG data as the ground truth, the evaluations might be skewed by variability observed during the setup protocols such as electrode placement and the participant's movement choice. One common method to overcome this is to normalize muscle activation by obtaining the maximum voluntary contraction (MVC). However, this will require the participants to perform activities to identify MVC values. Thus, variance will persist since the setup protocols for the collection of sEMG data are identical.

Another factor that affects our results come from the lack of model parameters. Since accurate mass and inertial properties for particular bone segments are difficult to obtain, most models leave these parameters as zero, and the resultant muscle activation does not account for this. Furthermore, static optimization assumes the system state is in equilibrium, not considering other dynamic forces in continuous states such as Coriolis effects and muscle-tendon dynamics.

One limitation of performing numerical analyses with a redundant model is the inability to account for co-contracting muscle pairs. To highlight this effect, the participant voluntarily co-contracted their arm during the same water drinking motion. The resultant difference between the optimized muscle activation and the sEMG data can be seen in Figure 4, highlighting the limitations of these solutions when using the musculoskeletal model.

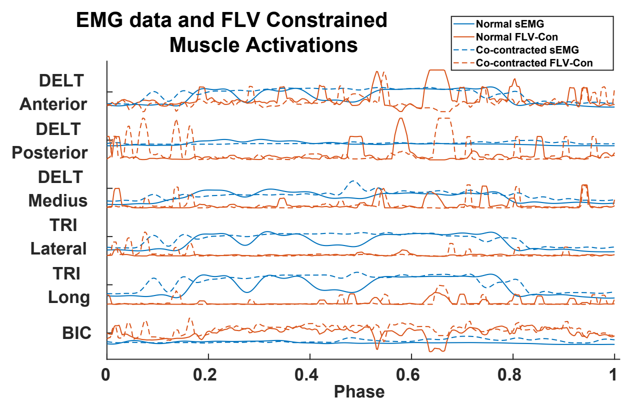


Fig. 4: Results from a water drinking motion in *voluntary* relaxed and co-contracted states.

The role of antagonistic muscle pairs has long been thought to be critical in controlling human body impedance. To translate this into numerical methods when solving muscle activation, more information is required to take these muscle pairs into account. Future work will incorporate a model that correlates the grip strength of the hand to voluntary co-contraction levels across the forearm. The vision is to take these additional constraints into account during calculations.

IV. Conclusion

This paper presented a preliminary validation to a musculoskeletal model that is widely used in research. A comparison of optimized muscle activation trends against real-world sEMG data was conducted. Results suggest that the model reflects the behavior of the human upper limb, with a consensus in muscle activation trends.

Future work will investigate the use of additional information to address co-contractions, and seek to overcome some assumptions in this work. Future trials will engage more participants to bolster confidence in the model for future applications such as rehabilitation assessment and assistance-as-needed robotics.

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