Implementation of Proprioception to Musculoskeletal Model

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Abstract

The mechanism by which the brain generates muscle-proprioceptive patterns remains largely unknown. Proprioception is essential for reflexes and coordinated human movement, yet its integration into physiological and mathematical models of the musculoskeletal system has been insufficiently explored. Moreover, the role of proprioceptive feedback in biomechanical assessments of muscle forces has been significantly overlooked. This study addresses these gaps by developing conceptual upper limb musculoskeletal model incorporating afferent signals from proprioceptors. The model was evaluated alongside one accounting for efferent signals from the central nervous system. Comparative analyses using inverse dynamics and optimization approaches demonstrated consistent results for both optimization criteria. Furthermore, experimental validation with EMG data from 15 participants performing identical movements confirmed the model's accuracy, highlighting its potential for enhancing our understanding of neuromuscular control and its applications in biomechanics.

Keywords: muscle activity, musculoskeletal model, proprioception, inverse dynamics, static optimization

1 Introduction

In biomechanics, one of the most important factors is muscle force and muscle activity. Understanding joint and bone loading, movement, and their pathology requires knowledge of muscle forces and joint contact forces (Asghari et al., 2023; Liu et al., 2024). Muscles are force generators that are regulated according to the reflex arc theory (Ivancevic et al., 2010). They can be compared to an actuator. It is an output device that can perform an action based on some input signal. Similarly to muscles, an actuator can have sensors that measure the force's magnitude. In the human body, these sensors are called proprioceptors (more precisely Golgi Tendon Organs) (Papaleo et al., 2023). Proprioception is the ability of the nervous system to detect changes that occur in muscles and inside the body through movement and muscle action. Studies only use efferent pathways and only address the issue of muscle activation at this time. They do not consider the information the brain receives in return or the fact that the brain must somehow process that information. As proprioceptors that sense muscle loading, the Golgi tendon organs are utilized in this study to examine afferent pathways. This study aims to investigate whether the common optimization approach of minimizing squared muscle activation can be replaced with the minimization of the Hill-Langmuir function to obtain more physiological results. To achieve this, a conceptual elbow quasistatic musculoskeletal model based on the Hill muscle model is developed.

2 Methods and Models

The musculoskeletal model of the elbow joint with three muscles was selected for this study. The two flexors are the m. biceps, m. brachioradialis, and the one extensor the m. triceps. The upper limb consists of the upper arm in its natural position next to the body and the forearm and wrist, which are rigidly joined to form a single segment. The elbow joint model only had one degree of freedom, and the shoulder joint did not move at all. A harmonic function with a cosine waveform is used to define the elbow motion (Watson, 1993):

$$\delta(t) = \delta_m + \delta_a \cos(\omega t) \tag{1}$$

It begins in full extension in time *t=0 s* with the forearm along the body, moves into full flexion at time *t=1 s*, and then returns to full extension at time *t=2 s*.

2.1 Hill Type Muscle Model

The musculoskeletal model of the elbow joint is based on the Hill-type muscle model (Vilímek, 2007; Cadova et al., 2014). This three-element model is a representation of the muscle mechanical response. The model consists of a muscle and tendon, which are presented as idealized mechanical objects. In this case, the muscle consists of an active force generator and a parallel passive component (Figure 1).

In this model, the total force of the complex is the sum of the passive and active forces, expressed by the equation (Cadova et al., 2014):

$$F^M = F_0^M (f_L^a \; f_v \; a(t) + f_L^p) \cos(\alpha) \tag{2}$$

The equation for the active force-length relation of the muscle is computed as follows (Martin and Schovanec, 1999):

$$f_L^a = 1 - ((L^M / L_0^M - 1)/0.5)^2 \tag{3}$$

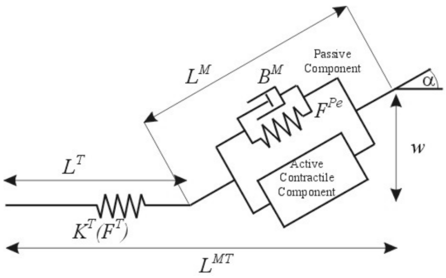

Fig. 1 Hill's muscle model structure Martin and Schovanec (1999)

where L^M is the actual muscle fiber length and L_0^M is the optimal muscle fiber length. The passive force-length of the muscle is computed as follows (Vilímek, 2007):

$$f_L^p = \left(\frac{L^M}{L_0^M}\right)^3 \exp\left(8\,\frac{L^M}{L_0^M} - 12.9\right) \tag{4}$$

The relationship between muscle force and contraction velocity for eccentric contraction is calculated using the following equation (Cadova et al., 2014):

$$f_v = \frac{2\,v_0^M - b' + \frac{v^M a'}{F_0^M}}{v_0^M - b'}, \tag{5}$$

where a' is constant equal to $-0.284\ F_0^M$, b' is constant equal to 11.51 mm/s, $v^M = \frac{\dot{L}^M}{0.1}$ is actual shortening/elongation velocity, and $v_0^M = \frac{L_0^M}{0.1}$ is maximal velocity of shortening/elongation. The relationship for isometric contraction is defined by the equation (Martin and Schovanec, 1999):

$$f_v = \frac{v_0^M - v^M}{v_0^M + c\ v^M} \tag{6}$$

2.2 Inputs Optimization

For solving the muscle redundancy problem, the static optimization methods are presented. At first, here is described the optimization of input information going from the brain to the muscles (Figure 2). In this scenario, there is a quasistatic inverse kinematics problem when the motion of the mechanism and the external forces are known, and we are looking for the resulting muscular propulsion effects. Minimization of activation squared was chosen for this static optimization (Tsikaros et al., 1997). In general, the optimization problem was to minimize the objective function $J = min$ over $i = 1 - n$ muscles, $n = 3$, with one equality constraint.

$$J_1 = \min \sum_{i=1}^{n=3} a_i^2 \tag{7}$$

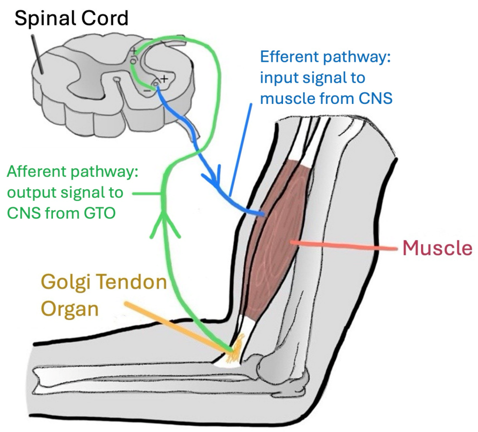

Fig. 2 Scheme of neuromuscular information flow

$$M = \sum_{i=1}^{n=3} r_i \; F_i^M \tag{8}$$

where r_i is the moment arm of the *i-th* muscle to the elbow joint, M is the elbow joint moment, and $a_i \epsilon <0; 1>$ is muscle activation of the *i-th* muscle, which is set as a boundary of the optimization.

2.3 Outputs Optimization

There is described an optimization of output information going from the muscles to the brain. It is based on musculoskeletal models that are founded on a common optimization criterion *"regulating muscle activity to achieve the minimum overall signal to the CNS from Golgi tendon organs"*(Daniel, 2004) (Figure 2) .This model described the Hill-Langmuir equation. In general, the Hill-Langmuir equation itself reflects the tissue response to the physiological output of the system, such as muscle contraction. The Hill-Langmuir equation is a special case of a rectangular hyperbola that can be expressed with the Hill-type muscle model as follows:

$$J_2 = \sum_{i=1}^{n=3} \frac{1}{1 + \left(\frac{F}{2F_{max}}\right)^k}; \quad k = 1, 2, 3, 4 \tag{9}$$

where a_i represents the activation of muscle and k is the Hill coefficient. This optimization criterion has the same equality constraint (8) and also the same boundary. The outcome of this function generates a sigmoidal curve (Figure 3). In our case, it represent a response of muscle activation.

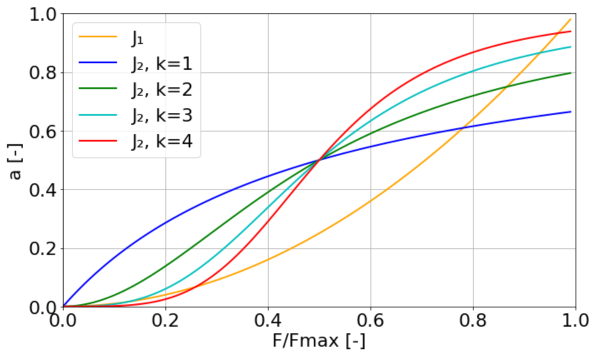

Fig. 3 Comparison of objective functions

2.4 EMG Measurement and Data Analyses

Surface EMG measurements were used on 15 probands to compare theoretical data with experimental data. It was used with two Shimmer 3 ECG units to measure muscle activity during elbow flexion motion without added weight. The experiment included probands aged 23 to 42 years. The conditions for participation in the experiment were as follows: absence of any acute illness or injury and absence of any past illness or injury in the upper limb area. Characteristics of probands were height: $179,2 \pm 10,6$ cm, weight: $72 \pm 15,3$ kg, and age: $27,8 \pm 5$. All measurements were made on the dominant upper arm with a sampling frequency of 256 Hz. The probands first performed a maximum isometric contraction for each muscle, followed by ten consecutive repetitions of elbow flexion-extension.

The data were exported to Python, where band-pass filtering was performed to retain signals with frequencies between 20 and 120 Hz. The absolute values of the filtered signals were then computed. Next, the root mean square (RMS) was calculated using a defined time window. All EMG signals from each muscle were normalized to the value of the maximum isometric contraction.

3 Results

This section presents the outcomes of the musculoskeletal model evaluation, focusing on comparisons between theoretical models and experimental data obtained through surface EMG measurements. The results demonstrate the differences between two optimization approaches—input optimization (minimization of activation squared) and output optimization (Hill-Langmuir model) as well as the alignment between theoretical predictions and experimental EMG data. The study provides insights into the activation patterns of elbow flexor and extensor muscles during flexion-extension movements.

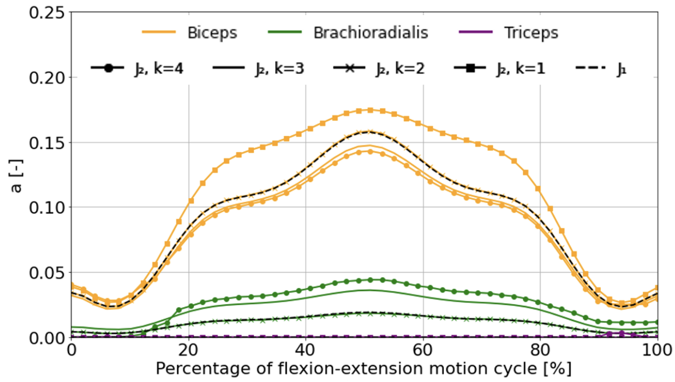

Fig. 4 Optimized muscle activation for both models.

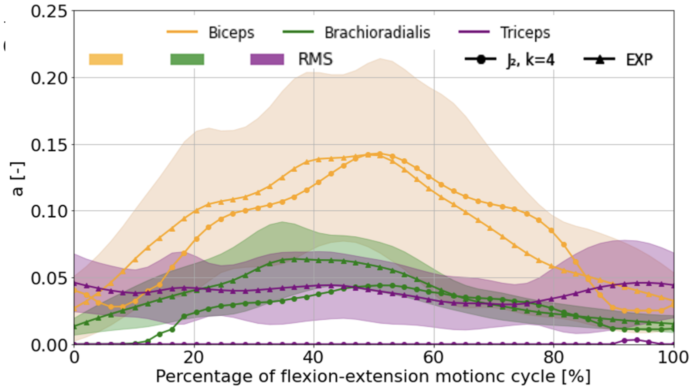

Fig. 5 Theoretical and experimental muscle activation.

3.1 Comparison of Optimization Models

Figure 4 illustrates the theoretical muscle activation profiles generated using two optimization approaches: input optimization, which minimizes the sum of squared activations, and output optimization with varying k indices, based on the Hill-Langmuir model. The results indicate that the differences between these two approaches are minimal and nearly negligible throughout the entire movement cycle. The most physiologically accurate result is observed with the Hill-Langmuir model at $k = 4$. This model prioritizes the lowest activation of the biceps brachii muscle, which is compensated by the highest activation of the brachioradialis muscle. The coactivation of muscles is the biggest with k=4. On the other hand, the Hill-Langmuir function with k=1 shows the highest activation of the m. biceps brachii, while the m. brachioradialis is not activated throughout the entire motion cycle.

3.2 Theoretical Predictions vs. Experimental Data

Figure 5 compares the muscle activation patterns predicted by the Hill-Langmuir model (k=4) with experimental data from surface EMG measurements. The experimental data, presented with standard deviations, were normalized to the maximum isometric contraction for each muscle to allow direct comparison. Theoretical predictions align well with experimental data during the mid-range of the flexion-extension motion cycle, validating the Hill-Langmuir model's ability to replicate physiological muscle activation with high accuracy. Minor deviations are observed at the extremes of the flexion-extension cycle, where standard deviations highlight variability in the experimental data. The biggest deviations between theoretical and experimental data are observed at m. triceps when Hill-Langmuir model is unable to reflect muscle patterns during human body movements where coactivation of agonists and antagonists occurs simultaneously.

4 Discussion

The conceptual quasi-static musculoskeletal model of the elbow joint with the implementation of proprioception is presented. It shows an opportunity to substitute the common optimization approach (minimizing squared muscle activation) with minimizing the Hill-Langmuir function. The predicted muscle activation pattern using the Hill-Langmuir function with k=4 shows better and more physiological results than the common optimization approach. Also, these results show good agreement with experimental data obtained from EMG measurements. Outcome from chapter 3.1 is further supported by Figure 3, which illustrates the progression of each function. Specifically, the Hill-Langmuir function with $k = 4$ shows a more gradual increase in muscle activation in response to increasing muscle force compared to the other functions.At lower force levels (0 to 0.2 on the x-axis), the red curve demonstrates minimal muscle activation, remaining almost flat. This suggests that the muscle does not react significantly to small changes in force, maintaining low activation levels.As the normalized muscle force increases beyond 0.5, the red curve exhibits a more pronounced rise, indicating a progressive and steady increase in muscle activation. This gradual behavior contrasts with the other curves, which show steeper or earlier activations at lower force levels. At higher force levels, we can also see that the red curve approaches a muscle activation value of 1, reaching its physiological limit, which it cannot exceed. Hill-Langmuir function is used to describe biological sensors. Typically, sensors in the human body operate in a way that they have a certain threshold value at which saturation occurs, beyond which no additional information is provided. Similarly, this applies to muscles, which can be described in this manner.This pattern reflects a model that prioritizes efficiency and minimizes unnecessary activation at low force levels, potentially aligning well with real muscle physiology.

The results from (Graves et al., 2000; Date et al., 2021) show the relative corresponding course of flexor muscle activation with our results. Importance of implemenation proproception to musculoskeletal models also confirm conclusion from (Myers and Lephart, 2002) where is described senzomotoric role of shoulder stability. Capsuloligamentous structures in the shoulder not only provide mechanical restraint but also influence muscle activity through proprioceptive input from embedded mechanoreceptors. Injury-related proprioceptive deficits disrupt reflex activity and motor control, but surgical intervention helps restore these neuromuscular mechanisms.

The presented model was developed based on several simplifications. Initially, the problem was solved quasistatically and in two dimensions, while dynamic force effects were neglected. Additionally, several input parameters exhibit proportionally large variability, including maximum isometric force, optimal fiber length, as well as various constants and coefficients. It should also be noted that the SLSQP optimization method was selected for this study, which is primarily used for finding local minima (or maxima) of nonlinear functions. The musculoskeletal model was applied to a simple flexion-extension motion of the elbow joint, considering only the primary muscles. The selected muscles in the model were used for subsequent comparison with sEMG measurements. For a better comparison between theoretical and experimental data, a larger number of probands would be needed, along with a higher-quality sEMG device with a higher sampling frequency, ideally on a specially designed apparatus allowing for specific isolated movement.

5 Conclusion

This study focused on integrating proprioceptive feedback into a musculoskeletal model of the upper limb and comparing it with a traditional input optimization approach. The results demonstrated that the Hill-Langmuir model, which incorporates proprioceptive feedback, aligns closely with experimental data from surface EMG measurements, particularly in the mid-range of motion cycles. The minimal differences between the Hill-Langmuir model and input optimization validate the physiological relevance and computational efficiency of the Hill-Langmuir model.

However, the model shows limitations in accurately reflecting muscle patterns during movements involving simultaneous coactivation of agonists and antagonists, particularly in the triceps muscle. This limitation highlights the need for further refinement in proprioceptive feedback modeling to better capture the complex interplay between muscle groups.

Future work should focus on improving the Hill-Langmuir model to address its limitations, particularly in dynamic and multi-joint movements. Additionally, expanding the study to include more complex motions and a broader range of muscles could provide a deeper understanding of the role of proprioceptive feedback in musculoskeletal modeling. Incorporating real-time proprioceptive data into optimization algorithms may further enhance the accuracy of the model and its applications in biomechanical analysis and rehabilitation.

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