Development of a high-density EMG-driven Hill-type muscle model

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Summary

We developed a computational model of a muscle actuator composed of in-parallel Hill-type models of motor units (MUs) using as inputs the motor unit discharge times obtained from decomposed high-density surface EMG (HDEMG) signals. We then used the model to simulate isometric muscle contractions. This work extends the traditional Hill-type muscle models and enables further modelling possibilities such as HDEMG-based simulations and controllers.

Introduction

In computational muscle modelling, whole muscle dynamics are mostly described as a single functional MU modelled with a Hill-type model. This assumption requires lumping the MU neural contributions to a single control [1], that is dissociated from the physiological control of muscle forces, which limits the range of uses of these models. Recent advances in the acquisition and decomposition of HDEMG signals [2] open new possibilities for the definition and use of Hill-type models at the MU scale. In this work, we propose a multi-MU Hill-type muscle model driven by experimental motoneuron discharge times obtained from HDEMG recordings [2].

Methods

The time-histories of the discharge times $sp_i(t)$ of 32 identified MUs were obtained from blind source separation of HDEMG signals acquired during an isometric trapezoidal contraction up to 35% of the maximum force of the tibialis anterior (TA) muscle of a healthy subject (male, 27 years old, 189 cm, 77 kg) [2]. The whole muscle (Figure 1A) is modelled as 32 in-parallel Hill-type MU actuators. The excitation and activation dynamics of each MU are modelled using an updated Hatze's model [3] with parameters recalibrated using mammalian data. In this model, each neural discharge time $sp_i(t)$ fires a model of neural action potential which drives two cascading second-order differential equations of the dynamics of the muscle action potential (MAP) (excitation dynamics) and of the length-dependent calcium concentration transients in the sarcolemma (activation dynamics). The active state obtained from an adapted calcium-dependent 8-state model of cross-bridge attachment dynamics [4] scales a normalized isometric force-length relationship yielding the i^{th} MU normalized force. The following simplifying assumptions were made. The 32 identified MUs are representative of the population of recruited MUs at 35% maximum force and an exponential frequency distribution of the MU-specific maximum forces was considered. Accounting for the variation of optimal fibre lengths (l_0^M) with recruitment threshold, all MU dynamics are sub-l_0^M and passive parallel forces can be neglected. The contribution of the short tendon of the TA is for now neglected. Finally, the 32 output MU forces are linearly summed to yield a whole muscle force profile $F^M(t)$.

Results and Discussion

The time profiles of the MAPs $u_i(t)$ and active state $a_i(t)$ of each i^{th} MU (Figure 1A) could be simulated from the HDEMG discharge times $sp_i(t)$, yielding a simulated whole muscle force $F^M(t)$ (red trace, Figure 1B) resembling experimental results (green trace, Figure 1B). Delays in force onset will be corrected by identifying or simulating the dynamics of supplementary representative MUs.

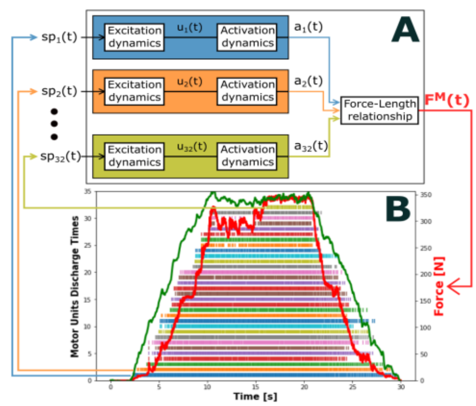

Figure 1: (A) Cascading dynamics of the 32-MU muscle model. B) Discharge times of the 32 identified MUs. Experimental transducer force (green). Simulated whole muscle force (red).

Conclusions

This new muscle modelling approach enables the use of decomposed HDEMG signals with Hill-type muscle simulations. Defining a multi-MU muscle actuator with MU-specific properties clearly separates excitation and activation dynamics. Ongoing work will consolidate the current model by mapping the sample of identified MUs to an estimate of the entire population of active MUs, reducing the number of simplifications and using ad hoc experimental data for neural inputs and model calibration and validation.

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