



Force estimation of electrically-stimulated rat gastrocnemius: comparison between an optimized biomechanical muscle model and bioimpedance measurements

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Abstract: In the present paper, we estimated the force exerted by the rat gastrocnemius using a biomechanical muscle model formulated from muscle dynamics. The muscle model input was the electrical excitation signal delivered in bursts of 12Hz, 22Hz and 32Hz. A set of seven parameters per muscle (medial and lateral gastrocnemii) was estimated using a genetic algorithm-based optimization that minimized the force calculated by the model and the directly measured force by a load cell. Resistance and reactance bioimpedance parameters were also measured synchronously with force. The optimization reduced the force RMS error of the model from 26 to 8%. The biomechanical model presented reliable force estimations, with a correlation $R=0.95$ ($P<0.01$). Resistance and reactance also provided highly correlated signals with the measured force ($R=0.91$ and $R=0.84$, respectively).

Keywords: *biomechanics, optimization, muscle force estimation, genetic algorithm, bioimpedance*

INTRODUCTION

The in vivo non-invasive muscle force estimation is a significant challenge in biomechanics, with numerous practical applications in clinics and sports. However, direct measurement is highly invasive. Alternatively, muscle forces can be estimated by combining analytical mechanical models, forward or inverse dynamics simulations, and parameter identification from experimental data. Muscle mechanical models have been widely used to estimate muscle forces (Erdemir et al., 2007). Electromyography (EMG) envelopes are obtained from raw data using low-pass filtering, which is associated with the overall excitation of a muscle. In the case of electrically stimulated muscles, the stimulus is input directly into the model passing through a nonlinear, s-shaped algebraic recruitment curve (Dorgan and O'Maley, 1997; Schauer et al., 2005). The neuromuscular excitation signals, either from experimental EMGs, electrostimulation or calculated by an open or closed-loop controller, are used to drive forward-dynamics muscle models, which allow estimating muscle's dynamic states: tendon force, activation and muscle length. Muscle models are based on elastic, damping and force-generation elements, taking into account muscle tissue constitutive relationships (contraction dynamics) and calcium metabolism with its interactions with the driving motor neuron (activation dynamics) (Zajac, 1989). Such models require defining dozens of parameters, some of which are the most sensitive (Carbone et al., 2016). Optimization techniques can reliably tune muscle model parameters from experimental data (Heine and Menegaldo, 2018).

Alternatively, muscle force information can be obtained from electrical impedance measurements of muscle tissue (Li et al., 2016). Electrical impedance myography (EIM) is an experimental technique that associates muscle electrical impedance with muscular activity (Rutkove, 2009). Using a rat gastrocnemius animal model, here we compare muscle force estimations obtained by two different techniques: mechanical muscle models and electrical impedance myography (EIM). Both estimates were validated against direct force measurements in vivo. The applied electrostimulation data used to evoke the rat gastrocnemius contractions were used as excitation inputs to a Hill-type muscle model as neural excitations. As a result, it was possible to compare three ways of estimating muscle force: bioimpedance, mechanical muscle modeling, and direct measurement by a load cell, as the gold standard. Such comparison will allow better understanding if the different approaches can generate reliable muscle force estimations, with many potential applications in neurophysiological studies of muscle control and clinics.

The Muscle Mechanics Model

We applied the same basic Hill-type muscle mechanics formulation developed by our group and used in numerous past publications for the present investigation. In Menegaldo and Oliveira (2009, 2012) and Oliveira and Menegaldo (2010), the reader will find the derivation of this model and how to estimate key model parameters. As a brief description, this formulation is based on the musculotendon model and uses the same notation of the seminal work of Zajac (1989). Zajac's original model comprised a contractile element and an elastic tendon. Its' key characteristic is the incorporation of the tendon mechanics, forming a musculotendon actuator, which effectively interacts with the skeleton,

generating joint torques through the moment arms and accelerating the body segments. Additionally, Zajac's model is dimensionless and uses a very robust notation that allows employing the same equations for virtually any somatic muscle. However, the original formulation is known for presenting numerical problems in deactivation, low activation levels and muscles with long tendons. To overcome them, elastic and viscous elements are introduced parallel to the contractile elements. Additionally, a bilinear differential equation (Piazza and Delp, 1996), in series with a nonlinear algebraic equation (A-model) (Manal and Buchanan, 2003), represents the activation dynamics. The entire model forms a nonlinear ordinary differential equation with the following states: tendon force, activation, and muscle length.

This model obeys the following terminology: the physical magnitudes of muscle (contractile element) force (F^M), length (L^M) divided by the dimensionless parameters: maximum isometric force F^{OM} (or force at the optimal length), optimal length L^{OM} (length which the muscle produces higher isometric force), respectively. L^T , L^M , and L^{MT} lengths stand for the tendon, muscle and musculotendon. α is the muscle fiber pennation angle. The rat medial and lateral gastrocnemii nominal muscle parameters were obtained from the Rat Hindlimb Model: https://simtk.org/projects/rat_hlimb_model from the open software OpenSim. The two gastrocnemii (medial and lateral) were considered a single muscle in the experiments. Here, the same neural drive was used for both muscles, but they were simulated separately, and the forces were added later.

Muscle force and impedance measurements in an animal model

The experiments were carried out with male Wistar rats with body mass between 250g and 400g and aged between 2 and 4 months. The animals were anesthetized with 3% isoflurane, and later the left gastrocnemius muscle of the animal was exposed through a surgical procedure. After muscle exposure, the gastrocnemius tendon was attached to a force sensor through a thin inextensible cord. Needle electrodes were attached to the extremities and belly of the muscle to stimulate muscle contraction and capture the Electrical Impedance Myography (EIM) signal. The experimental protocol was submitted and approved by the Animal Research Ethics Committee of the Federal University of Rio de Janeiro under the number 019/15. Muscle force data (F), a load cell and a signal conditioning system developed specifically for this sensor were used. The electrostimulation system consisted of a buffer connected to one of the D/A outputs of a NI6252 board (National Instruments, USA) controlled by software developed in LabView. The system could generate a biphasic pulse between -2.5 and 2.5 volts, with a pulse width of 500 μ s and frequencies between 0.5 Hz and 1kHz. Here, monophasic pulses only were tested.

Muscle model optimization

A train of three pulse bursts during 6s in different firing frequencies (12Hz, 22Hz and 32Hz) was used to excite the rat gastrocnemius. The excitation, force and electrical impedance signals were recorded synchronously (Figure 1). The signals were edited to reach a more compact time series with a smaller interval between the bursts, making numerical optimization easier. Raw excitation signals were input into the muscle model with nominal musculotendon and activation dynamics parameters from OpenSim. Usually, excitation signals are low-pass filtered before driving muscle models. Here, we decided to preserve the original excitation signals. Otherwise, the waveform of the electrical pulses would become distorted. The L2 norm between the calculated and measured muscle force for the entire time series was used as a cost function of an optimization problem that sought to find a set of musculotendon and activation dynamics parameters for both gastrocnemii: T_{ac} (activation time), T_{deac} (deactivation time) and A-value for the activation dynamics; and tendon slack length (L^{ST}), F^{OM} , L^{OM} and α for the contraction dynamics. The optimization was done in Matlab using a genetic algorithm. Bound constraints were formulated for the optimized parameters to stay within physiological limits.

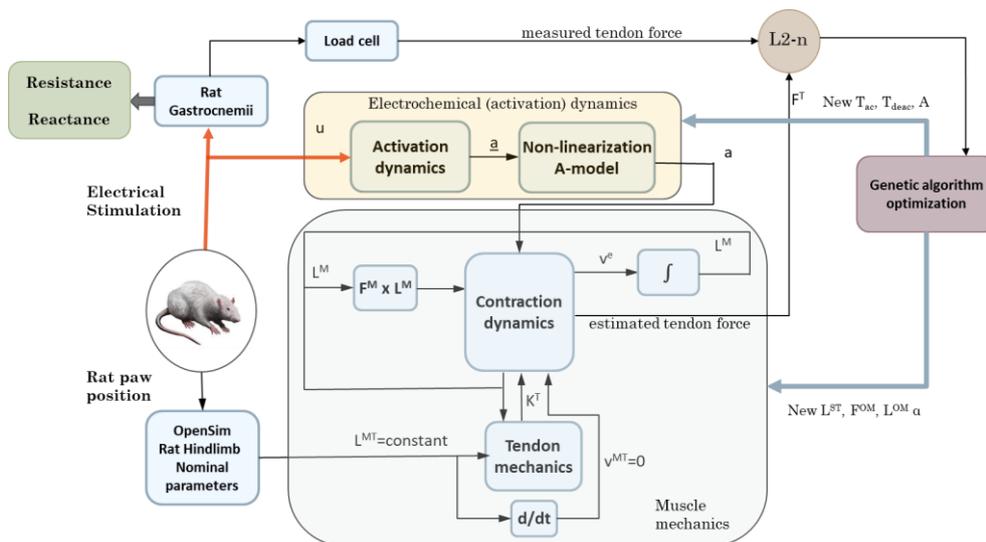


Figure 1: Optimization Problem formulation

Results and discussion

Figure 2 (right up) shows the excitation signal for the electrostimulation signal sample chosen for this work. Three bursts of 12Hz, 22Hz and 32Hz were used to evaluate the approach. At the right, the measured force from the load cell is presented. Below are the corresponding impedance measurements: the resistance, the real part of the impedance signal and the complex part reactance. All data is raw, with no filtering. Figure 3 (left) presents the electrical stimulation bursts and measured and simulated forces using the OpenSim nominal parameters. It can be observed that the simulated forces after the optimization largely improved their agreement with the measured force, with an RMSE of from 0.13(26%) to 0.04(8%). The low-pass effect of the activation and contraction dynamics generated a continuous waveform from the excitation pulses, which were reasonably spaced between each one at the studied excitation frequency.

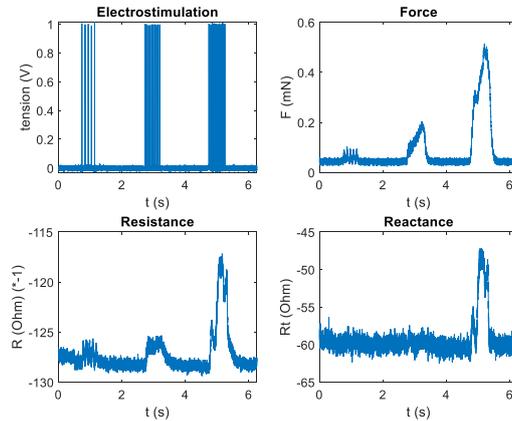


Figure 2: Upper row: electrostimulation signal and measured force by the load cell. The lower row, the corresponding bioimpedance measurements, the resistance the real part and the reactance the complex part of the signal.

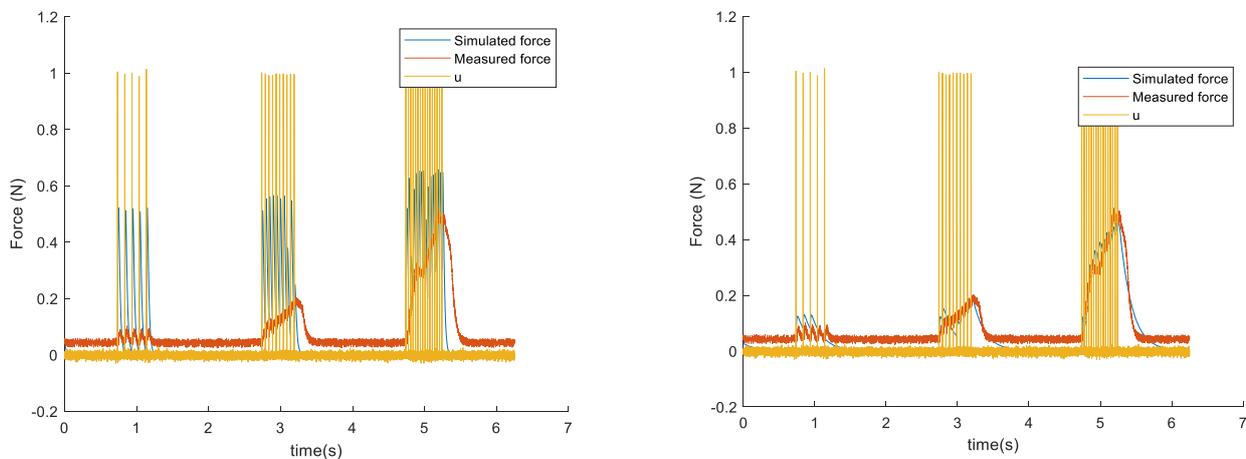


Figure 3: Electrostimulation, measured force and simulated force using the biomechanical muscle model. Left, the simulated force was obtained before the optimization for parameters identification. On the right, the simulated force was obtained using the identified parameters.

The correlation analysis performed among the four variables (measured force, simulated force, R and R_t) and shown in Figure 4 provided significant correlations ($p > 0.05$) among all variables. The largest correlation was observed between estimated and measured forces ($R=0.95$), followed by the resistance ($R=0.91$) and the reactance ($R=0.85$). The correlation between R and R_t was also very high ($R=0.93$). In conclusion, the optimized muscle biomechanical model can provide accurate muscle force estimations for the rat gastrocnemius in isometric, electrically stimulated contractions. However, the bioimpedance technique is promising, generating signals highly correlated with the measured force.

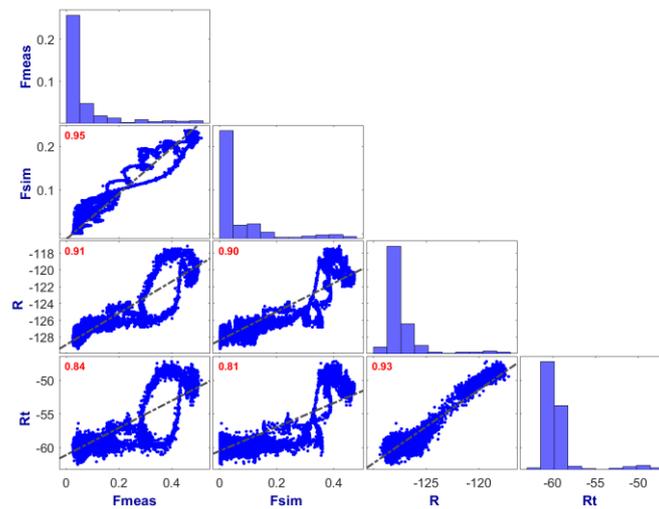


Figure 4: Correlation analysis among the measured force (F_{meas}), the model-calculated force (F_{calc}), the resistance (R) and the reactance (R_t).

ACKNOWLEDGMENTS

The authors acknowledge FINEP, FAPERJ, CNPq and CAPES for financial support.

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