The Effects of Flywheel Parameters on Rowing Exercise: A Predictive Simulation Study

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INTRODUCTION

Astronauts lose bone density and muscle mass due to the exposure to microgravity environment. Resistive exercise machines could reduce or even prevent these issues. The mechanical and geometrical elements of the device must be designed to achieve the desired loads on human tissue. During development, human testing can only be performed on Earth, and human performance may be different in the absence of gravity. In order to accelerate development, we propose to use musculoskeletal modeling to predict how humans perform exercise in a given mechanical environment, and determine tissue loads at the same time.

Here we demonstrate this concept on a model that includes a scaled down rowing machine and a single muscle. The effect of flywheel parameters on predicted movements and forces will be determined.

METHODS

System dynamics

A rowing machine includes a clutch mechanism that provides two phases with distinct dynamics. In our model (Fig. 1), a flywheel (m_1, c_1, k_1), a damper (b_2), and a spring (k_2) provide the resistance in the drive phase (1st phase). However, the damper (b_2), and one spring (k_1) will be disengaged in the recovery phase (2nd phase). Model parameters for a Concept 2 rowing machine (Table 1) were determined through a system identification based on literature data [1] and scaled down to the force and motion capability of the human forearm.

A 3-element Hill-based muscle model (Fig. 1) was employed to represent the human biceps brachii muscle, with parameters from [2]. Muscle dynamics was modeled with implicit differential equations for contraction and activation [3]. Muscle force was applied to the forearm (length L) via a moment arm d.

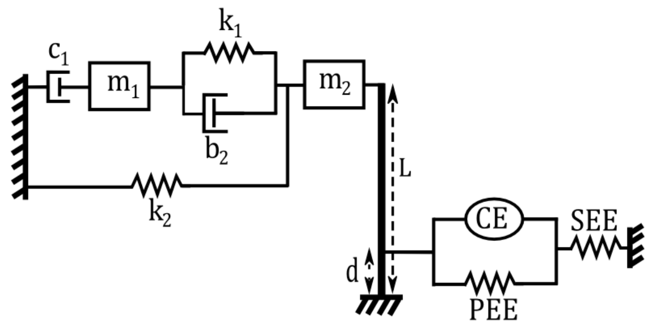

Figure 1. Schematic of the rowing machine, forearm, and biceps muscle.

The dynamic system model has six state variables: position (x_1) and velocity (v_1) of the flywheel, position (x_2) and velocity (v_2) of the arm, fiber length (Lce), and muscle activation (a). The control input is muscle neural control (u). From the rowing machine dynamics and muscle dynamics, six implicit dynamic equations were obtained and arranged in matrix form:

$$\mathbf{f}(\mathbf{x}, \dot{\mathbf{x}}, u) = 0,$$

where $\mathbf{x}$ is a vector containing the six state variables.

Simulation

The exercise task was defined as: achieve periodic arm motion with a prescribed amplitude and duration, leaving all other aspects of the performance free. It was assumed that a human would choose muscle control such that the task would be accomplished with minimal effort. Effort was defined as the integral of squared muscle excitation.

A Direct Collocation approach was used to find optimal state and control trajectories. The trajectories were discretized into $2N$ temporal nodes (N nodes in each phase). The midpoint Euler differentiation formula [4] was used to obtain $(2N-1)$ dynamics constraints. The cost function to be minimized was the mean of the squared muscle neural control:

$$J = \frac{\sum_{t_0}^{t_f} u^2}{2N}$$

In this particular case, 100 nodes were used in each phase. After time discretization, a nonlinear program (NLP) was obtained with 1402 unknowns and 1201 constraints. IPOPT was used as a NLP solver.

Three cases were examined to demonstrate the effect of machine parameters on predicted exercise performance. First, the original parameters from the system identification were used. Second, the parameters (m_1, c_1, k_1) were decreased by 50% to have a light flywheel with low resistance which is named as "Modified A". Third, all these properties were increased by 50% from their original values, and this case is labeled as "Modified B" (Table 1).

RESULTS AND DISCUSSION

The optimization predicted durations of the 1st phase and 2nd phase of 1.29 and 0.71 (s) respectively in the original rowing machine. Muscle activation and muscle force were almost constant in the phase 1. At the very end of the 1st phase, they drop to zero. At the end of phase 2, there is a sudden increase in muscle activation and force so the flywheel is accelerated without delay. The cable force shows a peak early in phase 1, and then drops to the zero for the rest of the time. This suggests that the optimal exercise strategy takes advantage of flywheel inertia.

The "Modified A" flywheel results in longer drive phase (1.44 s) and shorter recovery phase (0.56 s). As expected, the muscle is less activated during the 1st phase. Surprisingly, activation is increased in the second phase.

The larger flywheel inertia and damping in the "Modified B" machine causes a significant increase in muscle force. This increase in muscle force causes a shorter drive phase (1.15 s), and consequently longer recovery phase (0.85 s).

Future work will include validation of predicted exercise through human experiments, and extension of this approach towards a full-body exercise and a full scale rowing machine.

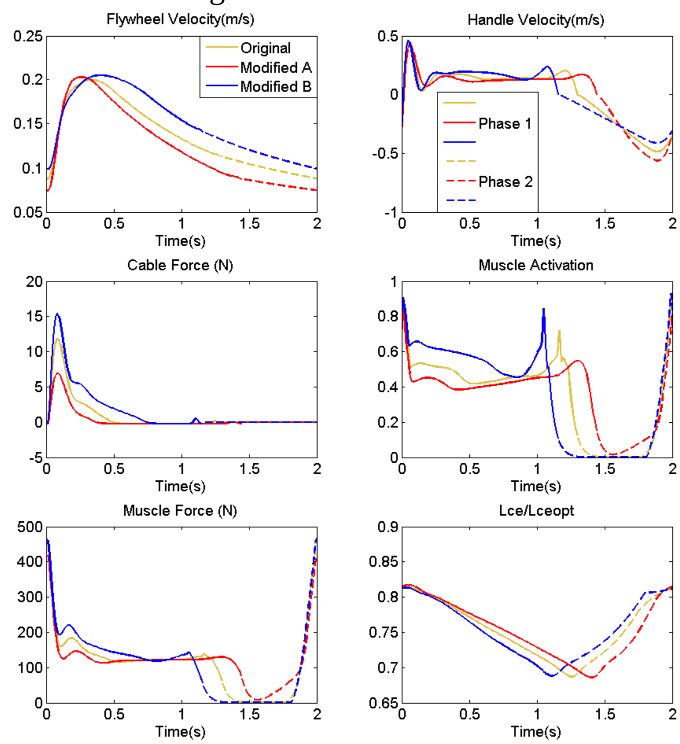

Figure 2. Selected variables from the predictive simulations. Lce is the muscle fiber length, and is expressed relative to the optimal fiber length (Lceopt).

REFERENCES

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Table 1: Model and muscle parameters

Parameters	k_1 (N/m)	c_1 (Ns^2/m^2)	m_1 (kg)	k_2 (N/m)	b_1 (Ns/m)	m_2 (kg)	d (m)	L (m)
Original	3046.07	70.14	66.12	31.98	186.76	1.1285	0.052	0.60
Modified A	1523.03	35.07	33.06					
Modified B	4569.10	105.21	99.18					