System Identification of Muscle Dynamics

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Summary

This study explores the use of Sparse Identification of Nonlinear Dynamics (SINDy) to model muscle dynamics during running. This algorithm produces a parsimonious representation of the system by identifying key terms that govern muscle behavior. We show that the model converges consistently to the same key terms and associated coefficient magnitude. Future work aims to correlate these findings with joint kinematics and EMG data, with the application of enhancing injury prevention and rehabilitation strategies.

Introduction

The benefits of physical exercise are numerous, including a decrease in cardiovascular disease [1], and an increase in emotional well-being [1], cognitive abilities [1], and bone health [2]. However, a risk of injury accompanies these advantages. The better we can understand the mechanics underlying movement, the more we can improve physical exercise interventions and identify potential injuries. We propose the use of nonlinear system identification on muscle dynamics data to cultivate this mechanical understanding.

Methods

System identification is performed by applying the SINDy (Sparse Identification of Nonlinear Dynamics) algorithm [3] to muscle data. SINDy utilizes sparse regression to identify a coefficient matrix that relates a function library to observed time series data. The function library forms a basis for the dynamical model of the system, and a sparsity threshold imposes a penalty on nonzero elements of the coefficient matrix to encourage a parsimonious representation of the data.

Muscle dynamics data is obtained using marker-based motion capture (Optitrack system). We place markers along the belly of four superficial muscle groups and use the piece-wise distance between markers as approximations for tissue deformations correlated with muscle contractions. This data is collected as a participant runs on a treadmill at fixed speeds. In addition to the motion capture data, we also collect force under the foot using force sensitive resistors (FSR).

The SINDy algorithm is applied to the approximate muscle lengths and their first derivatives, as well as FSR data (9 states variables). The derivatives are included to allow for an acceleration-based estimation of the dynamics. We iteratively fit the model to determine the optimal sparsity threshold and function library for our application.

Results and Discussion

Using optimized hyper-parameters, the SINDy algorithm is fit to muscle-dynamics data with an average R^2 value of 0.87 (Fig. 1). To avoid overfitting the data, these optimal hyper-parameters are determined based on accuracy of a test dataset. The optimal sparsity threshold to maintain model fidelity is 100, and the optimal function library (θ) is second degree polynomials, including interaction terms (Eq. 1).

$$\theta \triangleq \{1, x_i, x_i^2, x_i x_j\} \tag{1}$$

The identified nonzero coefficients (corresponding to terms most important to the dynamics), stay consistent as the sparsity threshold is increased. This suggests that the algorithm is accurately identifying key terms. Furthermore, the variance in coefficient magnitude decreases as sparsity is increased, which implies that not only are we narrowing in on the terms which define the dynamics, we are also gaining confidence in their magnitude.

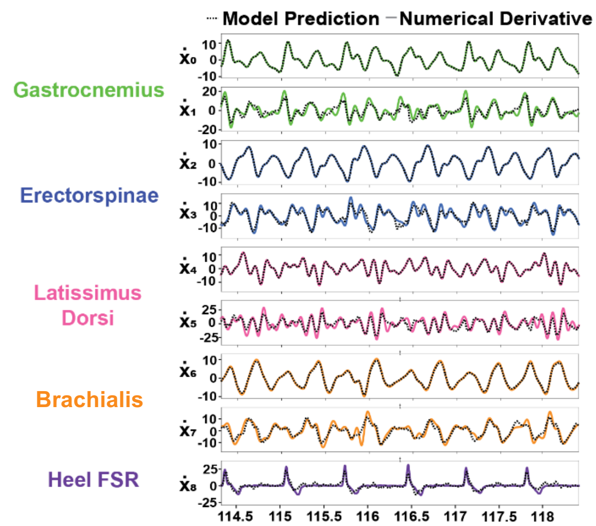

Figure 1: Representative example of the model fit.

Conclusions

SINDy applied to muscle dynamics data shows promise in its ability to reliably model the system. Next, we plan to compare the model coefficients to other biomechanical data such as joint kinematics and EMG to test for correlations.

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References

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