

Sensor-Driven Musculoskeletal Dynamic Modeling*

Laura A. Hallock¹, Robert Peter Matthew¹, Sarah Seko¹ and Ruzena Bajcsy¹

Abstract—The creation of a human dynamical model useful in upper-limb exoskeleton control remains an open problem. We present a framework that approaches model generation from a “sensor-driven” design perspective that explicitly avoids over-fitting parameters and minimally relies on literature values and biological assumptions. Initial results on synthetic data for a simplified model of the elbow indicate that this framework is a viable starting point from which to build more sophisticated dynamical models. Full results can be found in [1].

I. INTRODUCTION AND OBJECTIVES

A major obstacle to the creation of effective exoskeletal devices is our inability to model the dynamical properties of the system. Current models often use literature values, assumptions drawn from cadaver studies, and population measures. While there exist several “average human” modeling frameworks (e.g., [2]), these frameworks cannot accommodate significant musculoskeletal pathologies.

The ultimate goal of this research is to create a musculoskeletal model of the human arm that is *a*) simple and recoverable while accurately predicting the kinematics and dynamics of the system and accommodating pathology, and *b*) non-reliant on literature values or population measures. We assume the ability to measure skeletal kinematics, various morphological parameters, contact forces, and dimensionless, aggregate muscle “activation”.

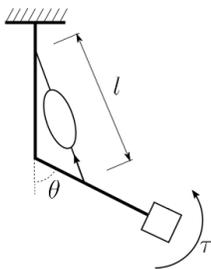


Fig. 1: Simplified human elbow model.

II. SIMPLIFIED MODEL

As a proof-of-concept, we consider the elbow in isolation, as shown in Fig. 1. For a full list of simplifying assumptions and a description of model dynamics, see [1].

To evaluate this model’s viability, we sought to determine whether, given known morphological parameters and a data

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¹L. A. Hallock, R. P. Matthew, S. Seko, and R. Bajcsy are in the department of EECS at UC Berkeley, USA {lhallock, rpmatthew, seko, bajcsy}@eecs.berkeley.edu

SNR (dB)	cond(W)	$\sum_{i=1}^3 \frac{ \beta_i - \beta_i^{fit} }{ \beta_i }$
100	591.0	0
10	624.2	0.0248
1	619.1	0.0472
1e-2	625.7	0.0309
1e-64	622.3	0.0341

TABLE I: Condition number of W and aggregate error of β_i for various signal-to-noise ratios. Condition numbers and error remain similar for varying levels of noise.

series of n normalized muscle activation-torque-angle tuples $(\bar{a}_j, \tau_j, \theta_j)$, $j \in \{1, \dots, n\}$, we could recover muscle force-length parameters. We write the dynamics as

$$\begin{bmatrix} \tau_1 \\ \vdots \\ \tau_n \end{bmatrix} = \begin{bmatrix} \frac{l_1}{l_{opt}^2} \sin \theta_1 \bar{a}_1 & \frac{1}{l_{opt}} \sin \theta_1 \bar{a}_1 & \frac{1}{l_1} \sin \theta_1 \bar{a}_1 \\ \vdots & \vdots & \vdots \\ \frac{l_n}{l_{opt}^2} \sin \theta_n \bar{a}_n & \frac{1}{l_{opt}} \sin \theta_n \bar{a}_n & \frac{1}{l_n} \sin \theta_n \bar{a}_n \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}$$

for muscle length l , optimal muscle length l_{opt} , and unknown muscle force-length parameters β_i . Using the implicit dynamics relation above, we assumed biologically reasonable values for β_i and swept through a range of τ and θ values to generate artificial \bar{a} values, added white Gaussian noise to each data series, aggregated the data into the regression matrix above, and fitted new β_i using least squares optimization. A complete description of this model recovery process can be found in [1].

To verify this optimization’s validity, we confirmed that the recovered β_i values were similar to those used to obtain the data, examined the condition number of the regression matrix W , and performed a numerical computation of base parameters ([3]). Results (Table I) indicate that our model is stable to perturbations in each data series and is thus a good starting point from which to build sophisticated models.

III. CONCLUSIONS

The model above is the first step toward a descriptive dynamical model of the human arm. Our tests indicate that the model is experimentally verifiable and has the potential to unify contact force data with internal human dynamics.

REFERENCES

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