A Gradient-Based Method for Automated Muscle Path Calibration

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INTRODUCTION

In musculoskeletal modeling, the path of a muscle is represented as a series of straight and curved lines, defined by origin, via, and insertion points as well as obstacles around which the lines wrap [1]. A correct configuration of muscle path is crucial for simulation accuracy as it determines muscle moment arm, on which a muscle's kinetic capacity is dependent. However, muscle path modeling can be laborious, where a large number of path-related parameters must be tuned; often manually. In this work, we propose a method that automatically calibrates muscle path, with high speed and accuracy.

METHODS

We formulate the process of parameter tuning as a least-squares problem with the following cost function:

$$\delta(\boldsymbol{p}) = \sum_{n=1}^{N} \|\boldsymbol{r}_{\text{data}}(\boldsymbol{q}_n) - \boldsymbol{r}_{\text{model}}(\boldsymbol{q}_n, \boldsymbol{p})\|_2{}^2 \rightarrow \min$$

where $\boldsymbol{p}$ denotes muscle path parameters, including locations of origin, via, and insertion points, as well as the size, location, and orientation of the wrapping obstacle(s), and $\boldsymbol{r}(\boldsymbol{q})$ is the moment arm at joint position $\boldsymbol{q}$. Note that $\boldsymbol{r}$ and $\boldsymbol{q}$ are vectors with the dimension of DoF number, whereas N is the size of the dataset.

To reduce computational load, we first take a geometric approach to compute $\boldsymbol{r}_{\text{model}}(\boldsymbol{q})$ from the muscle path defined by $\boldsymbol{p}$, and then specify the gradient of $\delta(\boldsymbol{p})$ in its analytical form. To this end, we revise the muscle path algorithm in [1] into a continuous form, such that the derivative $\partial\boldsymbol{r}_{\text{model}}(\boldsymbol{q},\boldsymbol{p})/\partial\boldsymbol{p}$ exists for all $\boldsymbol{p}$.

For result quantification, we use a 12-DoF human shoulder-arm model [2] as a reference to examine algorithm performance in replicating the geometry of all 42 muscle paths. Measurements of $\boldsymbol{q}$ in [3] are put into the reference model to generate artificial $\boldsymbol{r}_{\text{data}}(\boldsymbol{q})$ for calibration and validation.

RESULTS AND DISCUSSION

On a 2.9-GHz Intel Core i9 (64 GB RAM), the path calibration of all 42 muscles took 37.2 min; with parallel computing, the total time decreased to 5.5 min. For most muscles, the calibration took less than 1 min. Muscles with multiple via points and wrapping obstacles are configured with more than 18 parameters, requiring more iterations, but were still calibrated within 5 min.

The calibrated muscle path geometry shared much resemblance to the reference model (Figure 1, top). In validation, most muscles contain less than 1 mm of absolute error in moment arm about any actuating DOF (Figure 1, bottom); the mean is 0.37 mm.

With the analytical form of the gradient specified, our muscle path calibration method achieves speed and accuracy beyond manual capability. A major challenge in muscle path modeling is that a muscle may span multiple joint DoFs and have multiple moment arms, each determined by all actuating DoFs. Importantly, our method is not limited to fit moment arm–angle curves or surfaces but is designed to fit hypercubes. The path calibration we demonstrate is based on a vector of moment arms about 12 DoFs, which dependents on a vector of 12 generalized coordinates ($\boldsymbol{r}(\boldsymbol{q})$: $\mathrm{R}^{12} \mapsto \mathrm{R}^{12}$). This is an impossible task for manual tuning.

Though the performance is demonstrated in silico, the method is conveniently compatible with experimental data, since the only mandatory input is the relationship between moment arms and joint angles. We also derived the gradient for a path coordinate–based cost function, which enables calibration with medical imaging data (e.g., MRI) and expands the possibility of application.

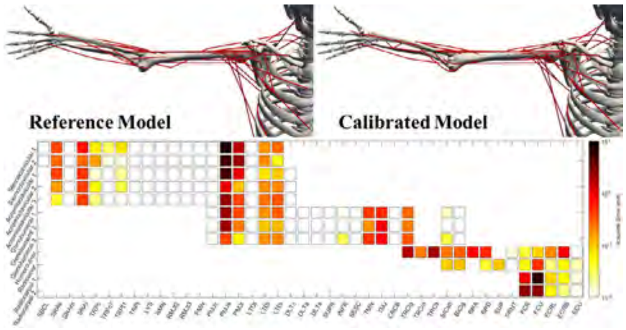

Figure 1 Top: Reference and calibrated muscle path geometry. Bottom: Absolute error of moment arm about each actuating DoF.

CONCLUSIONS

An automated method of muscle path calibration is developed with the gradient analytically specified, and its performance is demonstrated by fast and accurate replication of muscle path geometry.

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