A framework for forward-dynamics simulation of the human shoulder

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INTRODUCTION

A vast majority of the available biomechanical models of the human shoulder has been developed based on inverse dynamics, e.g. [1,2]. This imposes a number of limitations on their application. For instance, the glenohumeral joint is approximated as an ideal joint in an inverse-dynamics simulation. Therefore, the models fall short to predict the joint translations [3].

The different approaches developed to overcome the recurrent limitations of the models can be broadly divided in two categories. The first category tries to tailor an available inverse-dynamics model to a specific application, e.g. [3,4]. The second category aims to develop a framework allowing forward-dynamics simulation, e.g. [5,6]. Indeed, few studies have developed forward-dynamics simulations of the human body. In [5], dynamic optimization was used to develop a forward-dynamics model of the lower extremity. Dynamic optimization typically demands many times integration of the equations of motion. Given the computational expense incurred by the integrations, the method is impractical for common applications.

In this study, a framework for forward-dynamics simulation of the human shoulder is developed. In contrast with the dynamic optimization, the developed framework requires a single integration of the system equations. It is based on a joint application of a biomechanical model of the shoulder and a controller. The controller defines the muscle forces allowing the model to be simulated in forward dynamics. Different control scenarios are considered to investigate the model convergence in terms of accuracy and computational effort.

METHODS

Based on a given desired trajectory $\boldsymbol{q}_d$, the controllers generate the associated muscle forces ($\boldsymbol{F} + \overline{\boldsymbol{F}}$) to steer the biomechanical model, as illustrated in Fig.1. Each of the blocks shown in Fig.1 will be now elaborated.

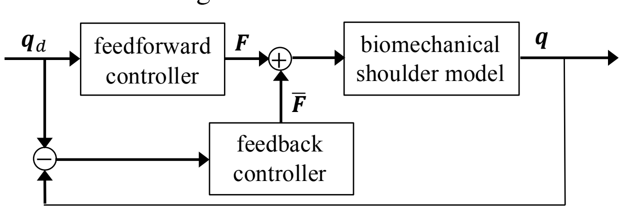

Figure 1: block diagram of the forward-dynamics framework.

Biomechanical shoulder model

A model of the glenohumeral joint with three rotational degrees of freedom is derived. The scapula motion is considered by the scapulohumeral rhythm. All the 11 major muscles spanning the joint are included in the model as massless taut ropes. The paths taken by the muscles during the joint motion are defined using the geometrical wrapping algorithm presented in [2]. Using Lagrange's equations, the equations of motion are derived:

$$(\dot{\boldsymbol{H}}_O - \boldsymbol{M}_O^{mg})[\boldsymbol{e}_i] = \left[\sum_{j=1}^{11} F_j(\boldsymbol{\rho}_j \times \boldsymbol{n}_j)\right][\boldsymbol{e}_i] \qquad \text{Eq.(1)}$$

where, $\boldsymbol{H}_O$ and $\boldsymbol{M}_O^{mg}$ are the angular momentum and the moment of the gravity force around the humeral head center, respectively. $[\boldsymbol{e}_i]$ is the partial velocity matrix. F_j, $\boldsymbol{\rho}_j$, and $\boldsymbol{n}_j$ are the magnitude, the lever arm vector, and the direction vector associated with the j^{th} muscle force.

Feedforward controller

The inverse system (if it exists) is always a candidate for the feedforward controller design [7]. Eq.(1), in compact form, can be written as

$$\boldsymbol{D} = [\boldsymbol{e}_i][W]\boldsymbol{F} \qquad \text{Eq.(2)}$$

where $\boldsymbol{D}_{3\times1}$ is the left-hand side of Eq.(1). $[W]_{3\times11}$ and $\boldsymbol{F}_{11\times1}$ are the moment arm matrix and the vector of muscle force magnitudes, respectively. By denoting $[\boldsymbol{e}_i][W]$ with the quasi moment arm matrix $[B]$, Eq.(2) appears to be a linear algebraic equation. Therefore, if the matrix $[B]$ has full row rank, one can define $\boldsymbol{F}$ associated with any given $\boldsymbol{q}_d$ by solving Eq.(2). However, given the indeterminacy of Eq.(2), in order to arrive at a nontrivial solution for $\boldsymbol{F}$, a static optimization routine is defined:

$$\begin{aligned} \text{min.} \quad & \boldsymbol{F}^T[E]\boldsymbol{F} \\ \text{s.t.} \quad & \boldsymbol{D} = [B]\boldsymbol{F} \\ & \boldsymbol{F}^{min} \le \boldsymbol{F} \le \boldsymbol{F}^{max} \end{aligned} \qquad \text{Eq.(3)}$$

where $[E]_{11\times11}$ is a weight matrix and $\boldsymbol{F}^{min}$ and $\boldsymbol{F}^{max}$ are respectively the upper and lower bounds on the muscle force magnitudes. The cost function is the sum of squares of the muscle stresses [1,6]. The optimization routine defines $\boldsymbol{F}$ such that it minimizes the cost, while satisfying the system dynamics (Eq.(2)) and the muscle-bound constraints.

Feedback controller

Having defined the muscle forces $\boldsymbol{F}$ by the feedforward controller (Eq.(3)), the biomechanical shoulder model, given by Eq.(1), can be solved numerically for $\boldsymbol{q}$. Ideally the resulted $\boldsymbol{q}$ has to follow the predefined $\boldsymbol{q}_d$. However, in practice the resulted $\boldsymbol{q}$ starts off following $\boldsymbol{q}_d$ reasonably well, but gradually loses accuracy as the time passes. More precisely, unless choosing a small enough stepsize for the simulation, accumulation of the successive errors due to the numerical integration causes the model response to drift away. However, the smaller the stepsize, the more computational effort is required. In order to ensure the model convergence for any reasonably large stepsize, a feedback controller is designed.

For the closed-loop system shown in Fig.1, the general form of Eq.(1) can be written as:

$$[M(\boldsymbol{q})]\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) + \boldsymbol{G}(\boldsymbol{q}) + [B](\boldsymbol{F} + \bar{\boldsymbol{F}}) = \boldsymbol{0} \qquad \text{Eq.(4)}$$

where $[M]$ is the inertia matrix, $\boldsymbol{C}$ is the vector of centrifugal force, $\boldsymbol{G}$ is the vector of gravity generalized force, and $\bar{\boldsymbol{F}}$ is the control input from the feedback controller. Given the simple nonlinear structure of Eq.(4), a feedback linearizing transformation is straightforward to derive [7]. Eq.(4) can be solved for $\ddot{\boldsymbol{q}}$

$$\ddot{\boldsymbol{q}} = -[M(\boldsymbol{q})]^{-1}\{\boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) + \boldsymbol{G}(\boldsymbol{q}) + [B](\boldsymbol{F} + \bar{\boldsymbol{F}})\} \qquad \text{Eq.(5)}$$

where the right hand side of Eq.(5) can be considered as $\boldsymbol{V}$, the new control input. This results in an equivalent linear system:

$$\ddot{\boldsymbol{q}} = \boldsymbol{V} \qquad \text{Eq.(6)}$$

We define the tracking error as $\tilde{\boldsymbol{q}} = \boldsymbol{q} - \boldsymbol{q}_d$. Letting

$$\boldsymbol{V} = \ddot{\boldsymbol{q}}_d - 2\lambda\dot{\tilde{\boldsymbol{q}}} - \lambda^2\tilde{\boldsymbol{q}} \qquad ,\lambda > 0 \qquad \text{Eq.(7)}$$

results in an exponentially stable closed-loop dynamics. Having defined $\boldsymbol{V}$, the control input $\bar{\boldsymbol{F}}$ can be achieved by substituting $\ddot{\boldsymbol{q}}$ from Eq.(6) in Eq.(4). Given the indeterminacy of Eq.(4), the same optimization routine as of Eq.(3) is performed to define $\bar{\boldsymbol{F}}$.

RESULTS

A smooth motion consists of 150° abduction combined with 70° flexion and 35° external rotation is simulated. The motion is performed in 7.2 [s]. The Runge-Kutta-Fehlberg method, which combines a fourth and a fifth order Runge-Kutta scheme for error control is used to solve the differential equations [8].

The model response with the feedforward-only controller is shown in Fig.2 for three different stepsizes (0.00001, 0.0001, and 0.01). The response starts off following the given motion but it becomes far apart, except for $T_s = 0.00001$. At this resolution the model response is almost indistinguishable from the given motion. This simulation took 6.5 [hrs] of CPU time on a 3.4 GHz processor with four cores.

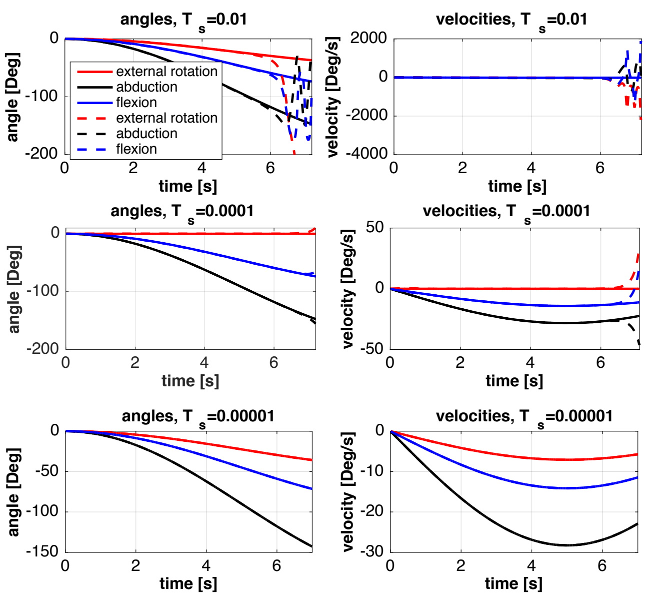

Figure 2: system response with feedforward-only controller, desired trajectory: solid line, system response: dash line.

The model response with the feedback+feedforward controller is shown in Fig.3 for two stepsizes (0.01 and 0.1). Comparing to $T_s = 0.01$ with the feedforward-only controller, the tracking accuracy is phenomenally good while it takes roughly the same computational effort (135 [s]). The model response for $T_s = 0.1$ provides an acceptable tracking performance. However in comparison with $T_s = 0.0001$ of the feedforward-only controller, it requires 393 times less computational effort.

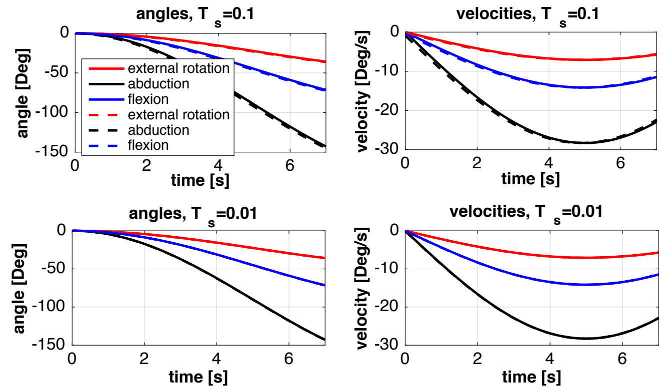

Figure 3: system response with feedforward+feedback controller, desired trajectory: solid line, system response: dash line.

DISCUSSION AND CONCLUSIONS

A framework for forward-dynamics simulation of the human shoulder was presented. It consisted of a biomechanical model of the shoulder that was simulated in forward dynamics based on the muscle forces defined by a controller. Two different control scenarios were considered. The joint application of the feedforward and feedback controller showed excellent tracking performance even for a reasonably large simulation stepsize ($T_s = 0.1$). However, the feedforward-only controller could not exhibit the same order of accuracy even with 393 times more computational effort.

The developed forward-dynamics simulation provided a straightforward solution to the recurrent limitations of the available inverse-dynamics models. We will further develop the study by incorporating a more sophisticated shoulder model and accounting for the glenohumeral joint translations.

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