Realistic Prediction of Human Arm Movements in Daily Activities Using Nonlinear Model Predictive Control

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Summary

Optimal control and predictive simulations have provided valuable insights into human arm reaching movements. However, few studies have explored realistic 3D arm models, primarily focusing on point-to-point reaching. In this study, we investigate voluntary human movements in realistic, three-dimensional tasks, such as drinking, to better understand motor control in activities of daily living. We employ a model predictive controller (MPC) that incorporates feedback, enabling the emergence of naturalistic arm trajectories. Our approach allows for real-time adaptation to dynamic environments, capturing the complexity of musculoskeletal dynamics. We demonstrate that with our approach we can accurately reproduce activities of daily living in good agreement with recorded experimental data from healthy participants. In the future, this approach will be integrated with wearable sensors to predict motor intention for assistive devices. We hypothesize that this will facilitate the development of human-machine interfaces with more intuitive and natural control.

Methods

A Musculoskeletal Model

A 3D-musculoskeletal arm model is used based on a previously published arm model and adapted to the MuJoCo physics engine [1, 2]. It consists of 7 Degrees of Freedom (DoFs) and is actuated by 24 muscles, modelled as Hill-type muscles with a rigid tendon. It is initialized to a relaxed resting position, with the elbow joint set to 90°, corresponding to a starting position on a table, for example reaching for a glass of water. The simulation time is set to 1.5 s, equivalent to the experimental data.

B Control

A trajectory optimization problem is set up, to generate muscle stimulation commands u. This problem is solved repeatedly in a receding-horizon fashion, with varying prediction horizons and recursively apply on the first element of the predicted optimal control sequence. Each control step, the optimization problem is warm-started by relying on previous best policies. The predicted trajectory of the arm model evolves solely from the dynamics of the musculoskeletal arm model. We state the optimization problem for the cost function J and state x as follows:

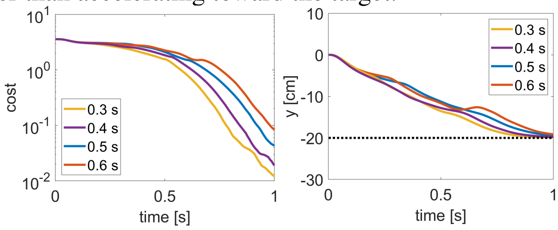
$$\begin{aligned} \min_{\pi_k} J &= \min_{\pi_k} \sum_{k=0}^{N} l(x(k), u(k), k), \\ \text{subject to } \; x(k+1) &= f(x(k), u(k), k), \\ u(k) &= \pi_k(x(0), ..., x(k)). \end{aligned} \tag{1}$$

C Experimental Data

We used a previously published dataset, that recorded upper limb movements of 20 healthy individuals performing diverse activities of daily living such as drinking or eating [3]. We compared the recorded optimal marker positions and inertial measurement units to the simulated marker positions and accelerations in the model.

Results and Discussion

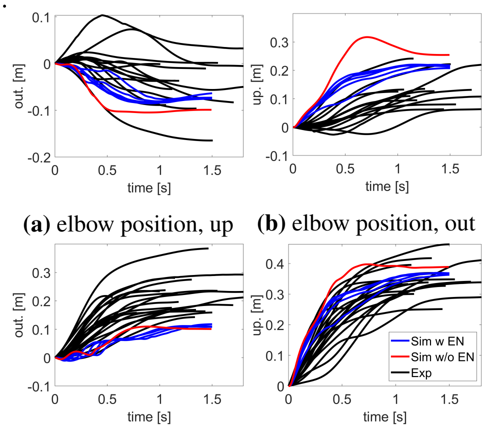
We investigate the influence of model predictive control (MPC) parameters on healthy arm-reaching movements, particularly the effects of prediction horizon length and different optimality principles. Our findings reveal three key effects. First, increasing the prediction horizon from 0.3 to 0.6 s results in more cautious and slower movements—even with the same movement end time—as the model better anticipates future states and distributes effort more evenly, rather than accelerating toward the target.



(a) cost **(b)** wrist position

Figure 1: Simulated cost and wrist position for a simple reaching task, while varying the prediction horizon length

Second, while simple cost functions suffice for point-to-point reaching in the transverse plane, more complex 3D lifting movements, such as drinking or bringing a glass to the mouth, require additional cost terms. Specifically, incorporating energy efficiency penalties prevents excessive elbow elevation (see Fig 2b, blue compared to red curve). Finally, our model predictive control approach successfully predicts reaching movements in strong agreement with experimental data (see Fig. 2, blue compared to black curves).



(a) elbow position, up **(b)** elbow position, out

(c) wrist position, up **(d)** wrist position, out

Figure 2: Simulated and experimental marker data for the drinking task (wrist and elbow marker, for the simulation 5 repeated runs are shown)

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References

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