Predictive Simulation of Reaching to Moving Targets using Nonlinear Model Predictive Control

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The human central nervous system (CNS), consisting of brain and spinal cord, coordinates the kinematics and kinetics of body motions. In a goal-directed reaching task, where only the target position is known, the CNS finds a unique and optimal trajectory among all possible trajectories and muscle activation patterns. In this research, a nonlinear model predictive controller (NMPC) with a moving prediction horizon is used to simulate the CNS trajectory planning and execution for goal-directed motions. The NMPC is able to consider the non-linear dynamics of the body's neuromuscular system to provide more realistic predictions. In addition, the optimal trajectory is predicted over a finite horizon that resembles the prediction properties of human motor control. The NMPC is a simultaneous control method because the optimal trajectory and its required muscular activities are calculated at the same time.

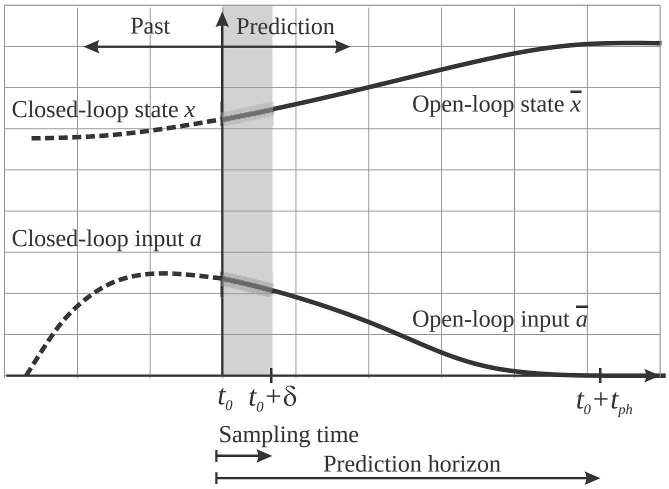

Figure 1: The solid lines show the optimal muscle activation ($\bar{a}$) and state trajectories($\bar{x}$) in the given prediction horizon.

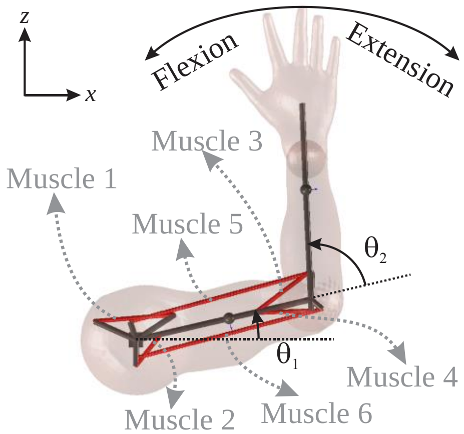

Figure 2: A schematic view of the planar arm model

The NMPC uses a control-oriented model (COM) to predict the optimal trajectory, and feedback information to correct the prediction errors. In this research, a planar arm model similar to the one developed by Ghannadi et al. [1] was used as the COM. This model consisted of a fixed torso, an upper arm, and a forearm connected by revolute joints. Six skeletal muscle groups consisting of shoulder and elbow mono-articular flexors/extensors and two bi-articular flexors/extensors were used to actuate the arm as shown in Figure 2. A modified Hill-type muscle model was used to simulate the skeletal muscle contraction dynamics.

The NMPC predicts the optimal dynamics of the system ($\bar{x},\ \bar{a}$) over a prediction horizon (Figure 1) by minimizing the following cost function:

$$J = \int_{t_o}^{t_o+t_{ph}} w_1\left(\zeta(t) - \zeta_{tgt}\right)^2 + w_2\, G^M\big(a\,(t)\big)\, dt \tag{1}$$

$$\text{subject to: } 0 < a(t) < 1 \tag{2}$$

where ζ and ζ_{tgt} are the hand position and its target position in the Cartesian coordinate system, $G^M\big(a(t)\big)$ is a physiological cost defined as $G^M = \dot{a}^2(t)$, and t_{ph} is the length of prediction horizon. w_1 and w_2 are the weighting coefficients as tuned via trial and error. The state variables at the current time (t_o) are obtained from the current sensory information. The input ($\bar{a}$) is an optimal open-loop solution over the prediction horizon. If there is no external disturbances and no model uncertainty in the system, with infinitely long prediction horizon, the open-loop solution can be applied to the system for all time $t > t_o$. However, for the finite horizon case and in the presence of noise and uncertainty, the open-loop solution should only be applied until the next sampling time $(t_i + \delta)$. At the new time step, the optimal solution is re-evaluated with the new initial conditions and iteratively applied to the system. Here, the optimal dynamics over the prediction horizon is calculated using an orthogonal collocation method [2]. This method is a direct (simultaneous) optimization method in which both states (x) and inputs (a) are parameterized and become part of a larger Nonlinear Programing (NLP) problem. By incorporating the feedback information, the NMPC is converted from a completely open-loop controller to an optimal closed-loop controller.

The NMPC constantly monitors the deviations from the optimal trajectory and the target position. Here, we study the case where the target position suddenly moves. The hand is initially at rest at point O (Figure 3) and moves towards the target at point A. Then, one second later, the target position suddenly moves to the point B. In this simulation, the time delay related to the visual cognition of this change (about 150 ms) has not been considered.

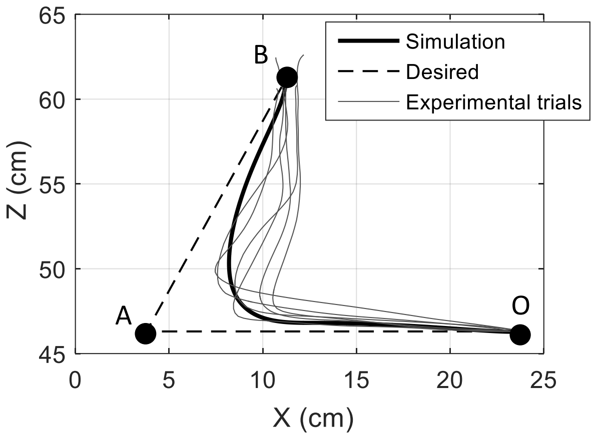

Figure 3: The hand trajectory when the target is suddenly moved from A to B

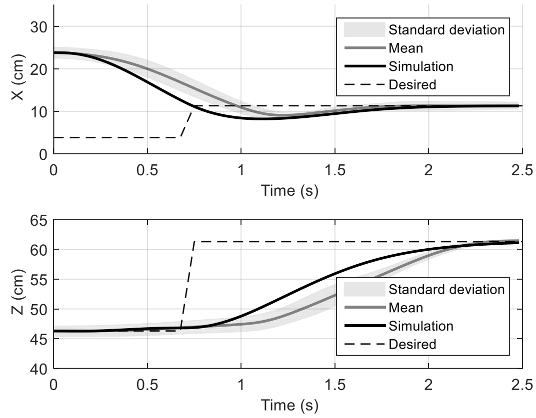

Figure 4: Displacement of hand in X and Z directions when the target is suddenly moved from A to B

As shown in Figures 3 and 4, the NMPC controller is able to track the target change of position and correct the hand trajectory to reach the new target. The NMPC results are in good agreement with the experimental trials performed in our laboratory and captured with a motion tracking system.

In this research, we presented a non-linear model predictive controller to mimic human motor control systems. The results showed that it can successfully replicate certain features of the human motor control system including path planning while handling the muscle redundancy, target tracking, and predictive behavior. The current implementation of this approach is computationally expensive. However, online NMPC methods such as Continuation/GMRES method [3] and advanced-step NMPC [4] can be used to achieve real-time performance.

References

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