

Optimization Criteria for Human Trajectory Formation in Dynamic Virtual Environments

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Abstract. Which criteria determine the formation of rest-to-rest arm movements when interacting with virtual mass-damper dynamics? A novel bilevel optimization approach is used to find the optimal linear combination of common optimization criteria for human trajectory formation such that the resulting trajectory comes closest to the human-performed one. The goal is to utilize this optimal combination to predict human motions in robot control. Experimental results show that a subject-dependent criteria combination can be found for different mass-damper dynamics.

Key words: Human trajectory formation, Bilevel optimization

1 Introduction

The question how humans form a rest-to-rest arm trajectory has attracted much attention in behavioral science. This knowledge is used, for example, for path planning algorithms of robot assistants in human-robot collaborative manipulation (HRCM) or for predictive control algorithms in teleoperation systems. The goal is in both cases to adapt the planning/control algorithms to the movements of the human by predicting his/her trajectory [2, 5, 7, 12].

Various research groups report invariant features for rest-to-rest movements, e.g. a bell-shaped velocity profile. To account for these invariant features, different optimization criteria were presented (see Sec. 2). Only little is known about the influence of external mass-damper dynamics on the arm trajectory formation. Many tasks, however, are performed under the influence of these dynamics, e.g. a common task in HRCM is to collaboratively carry an object. The influence of external dynamics was investigated, for example, by Luo *et al.* [4] for a constrained rotating crank experiment and by Svinin *et al.* [9] for flexible objects.

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Luo *et al.* explained the data as a combination of two cost functions, Svinin *et al.* used an optimization criterion for unconstrained motions.

In this paper we analyze rest-to-rest arm movements for different mass-damper dynamics acting on the human hand. Our approach is based on two steps: first, arm trajectories are recorded, and second, a linear combination of four common optimization criteria is computed that approximates the recorded trajectories best. A novel bilevel optimization approach [1], see Sec. 3, is used to find the linear combination of optimization criteria which yields a trajectory with minimal costs. The gained knowledge can be used to predict human arm trajectories, such that a path planning/prediction algorithm of an autonomous/teleoperated robot can be adapted accordingly. A basic assumption is that the end point of the movement is known or can be predicted from prior movements. The experimental setup, procedure and results are given in Sec. 4. The paper concludes with a summary and outlook in Sec. 5.

2 Models of Arm Motion

Arm and Muscle Dynamics. The biomechanical dynamics of the human arm is modeled to analyze human arm motion. Thus, the rigid-body dynamics describing the properties of the human skeleton is combined with an ODE-model approximating the dynamical behavior of human muscles.

Following the line of [8], standard rigid body dynamics is used to model a planar two-link human arm. Joint torques τ result from muscles forces f_m , joint damping and external forces. In our experiment these external forces are created by the virtual dynamics.

The arm model allows to include muscle dynamics where models of different complexity can be utilized, e.g. [8, 13]. The complete system of the human arm dynamics can be denoted by the first-order ODE $\dot{x} = h(x, u)$, where u is the control input and x the state that includes the joint angles q .

Optimization Principles. The approach is based on the assumption that human trajectories can be described as the result of minimizing an unknown cost function while accomplishing a predefined task. Since one basic criterion often does not reproduce all different trajectories well enough, we extend this assumption to the minimization of a linear combination of cost functions. As will be shown in the following, the linear combination of four common optimization criteria delivers an accurate description of our experimental data. Flash and Hogan [3] introduced the *Minimum Hand Jerk* cost function f_{HJ} using the Cartesian coordinates of the hand position $p(t)$. The resulting hand paths are fairly straight. A variation of this cost function is the *Minimum Joint Jerk* criterion f_{JJ} which yields slightly curved hand paths by directly utilizing the kinematics of the human arm

$$f_{HJ} = \int_{t_0}^{t_f} \left\| \frac{d^3}{dt^3} p(t) \right\|^2 dt, \quad f_{JJ} = \int_{t_0}^{t_f} \left\| \frac{d^3}{dt^3} q(t) \right\|^2 dt.$$

The *Minimum Torque Change* criterion f_{TC} proposed by Uno *et al.* [10] is the integral over the squared norm of the first time derivative of the torques τ in

the joints. As a variation we additionally consider the *Minimum Muscle Force Change* criterion f_{MC} utilizing the muscle dynamics directly. Note that the torques τ are the sum of the torques resulting from joint damping and external forces in addition to the torques caused by muscle forces f_m .

$$f_{TC} = \int_{t_0}^{t_f} \left\| \frac{d}{dt} \tau(t) \right\|^2 dt, \quad f_{MC} = \int_{t_0}^{t_f} \left\| \frac{d}{dt} f_m(t) \right\|^2 dt.$$

3 Optimization Problem

Mathematical Problem Formulation. The combination of the dynamics of the human arm and a cost function (cp. Sec. 2) yields a nonlinear optimization problem, *the lower level program*.

Another problem, *the upper level program*, is to find the cost function f out of a family of considered cost functions minimizing the distance d between the recorded human arm data p_{rec} and the computed arm data $p_{comp}(f)$ obtained by solving the respective lower level program. Only linear combinations with the weights $w_i \geq 0$ are considered here: $f = \sum w_i f_i$.

The combination of the lower and upper level program is a *bilevel program*.

Solution of Bilevel Program. The chosen direct optimization approach is based on discretization of the ODE $\dot{x}(t) = h(x(t), u(t))$, i.e. the ODE is transformed into the equation $H(\bar{x}, \bar{u}) = 0$ with the time-discretized state \bar{x} and control \bar{u} , such that the lower level program can be rewritten as $\min F(\bar{x}, \bar{u} | w_i = \text{const.})$ subject to $H(\bar{x}, \bar{u}) = 0$. Then the Kuhn-Tucker-conditions of the lower level program are utilized to transform the bilevel problem into a standard nonlinear optimization problem of the type $\min D(\bar{z})$ subject to $\bar{z} \geq 0$ and $C(\bar{z}) = 0$.

Here the interior-point algorithm IPOPT [11] is used to solve the problem. In [1] we analyze the performance of this approach and show that the results of the algorithm are reasonably close to the optimum.

4 Experimental results

In this section an experimental setup is presented to record human rest-to-rest movements under the influence of external mass-damper dynamics. For each recorded trajectory an optimal combination of optimization criteria is determined and the variations of the combinations are analyzed with respect to the different subjects and different external influences.

Experimental Setup. A 2 DoF haptic interface consisting of two linear actuators, where a Thrusttube module 2504 from Copley Controls Corp. is mounted at a right angle on top of a second Thrusttube module 2510, is used for the experiments. Each of the actuators is equipped with an optical position encoder (resolution 1 μm). A 6 DoF JR3 force sensor together with a handle is mounted on the upper actuator (Fig. 1). The haptic interface is controlled using a position-based admittance controller with force input, see [6] for details. Thus, the desired behavior of the device is obtained through the choice of the admittance gains virtual mass m_v and damping b_v .

The task consisted of rest-to-rest movements between two targets A and B, see Fig. 1. The workspace of the task was 0.29 m x 0.16 m. The targets and hand position were visualized in a virtual scene, which was presented to the subject via a head-mounted display. To decrease the coupling effects between task completion time and accuracy described by Fitt’s law a deviation of ± 1.5 cm from the target was allowed.



Fig. 1. Experimental setup: Photo and sketch of 2 DoF device

Eight mass-damper combinations ($m_v \in \{2, 4, 8, 12\}$ kg, $b_v \in \{0, 5, 10, 20\}$ Ns/m) were implemented and presented to the subjects in a randomized order. With each stimulus, 10 trials in a row were performed.

Position and force data were recorded at a frequency of 1 kHz. Three male and one female subject, all right-handed and aged between 23 and 27, took part in the experiment. The subjects’ chair was adjusted such that the handle was grasped at the height of the subject’s shoulder. The subjects were asked to make rest-to-rest movements as *naturally* (not as fast or as straight) as possible between the targets.

Results. For a proper analysis, the first trial of each stimulus was discarded to avoid after-effects of the previous one. Of the remaining ones, the two-thirds closest to the median of all 10 trials were selected for the analysis. The left plot of Fig. 2 shows one example of six selected trials.

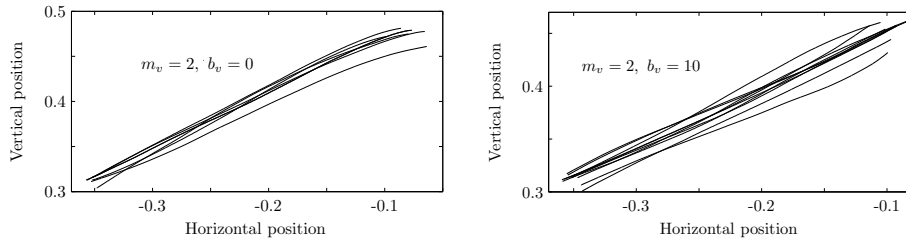


Fig. 2. Recorded human trajectories for different stimuli: Common structure for low relative damping (left) and no apparent scheme for high relative damping (right)

For our analysis the mean of the weight distributions (cp. Sec. 3) was calculated for each stimulus and subject. Our experiments show that the weight distributions differ between subjects with the same stimulus, but all by themselves are quite stable, i.e. the standard deviation is small compared to the general distribution of weights (cp. Fig. 3). Consequently, the one or two dominant criteria are found to be dominant in all considered trials. The differences between subjects

can be attributed to human variability. Although the task of performing natural arm movements was the same for all subjects, one subject may still focus more on making lines as straight as possible, while another subject may try to move with minimal effort. Also, biological parameters such as emotional state, time of the day, motor skills etc. can lead to variations between subjects. This finding implies, that an optimal weight distribution can only be used for a specific subject, but then we obtain a high prediction accuracy.

Furthermore, the trajectories can be explained for some stimuli as a combination of only two optimization criteria (cp. Fig. 3). The computations also reveal that the distances between the selected human trajectories and the computed optimal ones are smaller than one centimeter. This accuracy in combination with the

small variation will be useful to predict short-term future movements of a subject in his current state, such that the behavior of an autonomous/teleoperated robot can be adapted accordingly. Note that only a few test-trials are needed for self-calibration of such a control approach.

An increase of relative damping $\frac{b_v}{m_v}$ raises the variance of the trajectories of all subjects, compare Fig. 2 (left: small relative damping, right: large relative damping), such that for a high relative damping, e.g. $\frac{b_v}{m_v} = 5$, the weights seem to become random, compare Fig. 4 (left) with Fig. 3. Consequently, the selected trajectories cannot be explained soundly using one weight distribution.

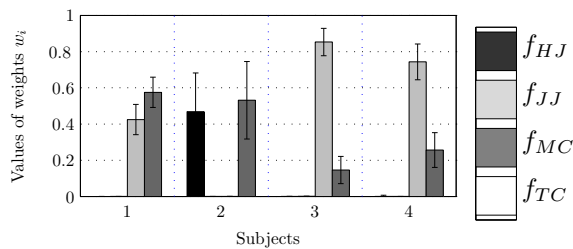


Fig. 3. Mean values with standard deviations for each subject [$m_v = 2, b_v = 0$]

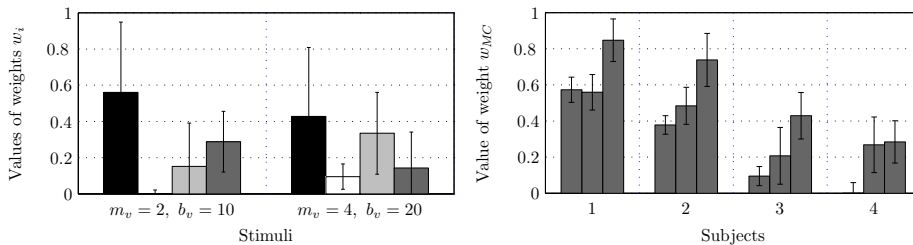


Fig. 4. Weight distributions of one subject for high relative damping with large deviations (left) and weights corresponding to f_{MC} for all subjects where $b_v = 5$ and $m_v \in \{2, 4, 8\}$ (right) [see Fig. 3 for color coding]

If the weight distributions of one subject are compared with respect to different stimuli, we could not determine a strong correlation between external dynamics and the resulting weight distribution. An increase in virtual mass m_v for constant damping b_v , however, tends to correlate with a larger weight corresponding to f_{MC} (e.g. Fig. 4 (right)). A possible interpretation is that for larger m_v the physically more demanding task results in taking muscle forces more into consideration.

5 Conclusion

We investigated rest-to-rest arm movements for different external dynamics. Utilizing the bilevel optimization approach the optimal combinations of cost functions were found to reproduce the recorded hand paths. Variation of the respective weights within a series of trials for one stimulus was found to be small if the trajectories exhibit similarities. Thus, by the presented approach a subject-specific weight distribution can be determined, which can be used to predict the next movement of this subject for identical external dynamics. For given mass-damper dynamics, subject-dependent weight distributions can be found. A strong general correlation between mass-damper dynamics and weight distribution has not been observed.

Future work consists in a larger behavioral study to confirm the results and in the implementation of path planning algorithms based on the found criteria.

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