Human Control of Complex Objects: Optimization or Submovements with Impedance?

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***Abstract*—Studies on the control of manipulation in humans have primarily focused on rigid objects. However, humans are also skilled at manipulating non-rigid objects possessing complex dynamics, like carrying a cup of sloshing coffee. Inspired by how humans dexterously carry a cup full of coffee without spilling, this study aims to understand what strategies humans use to control objects with internal dynamics. This task is especially demanding when performed quickly, where object dynamics dominate and sensory feedback is too slow for online corrections. In the experiment, subjects manipulated a two-dimensional cart-and-pendulum system in a virtual environment via a haptic robotic interface, where the cart represented the cup and the pendulum bob emulated the liquid inside the cup. Velocity profiles of the human movements were compared to those predicted by different control models. Two optimization-based models predicted two symmetric velocity peaks separated by a minimum that became negative as the cup movements became faster. In contrast, the experimental profiles displayed two peaks with significantly different peak values. The data also did not show a correlation between movement duration and the minimum velocity. Subsequent simulation studies showed that these features could only be reproduced by a submovement-based control strategy that included additional hand impedance. These results suggest that the combination of submovements and mechanical impedance, dynamic primitives, presents a competent description of human manipulation of complex objects.**

I. Introduction

Studies on how humans manipulate objects have focused on tasks such as grasping [1], lifting [2], and transporting [3] of rigid objects. Relatively few studies have examined human control of objects that contain internal degrees of freedom. Manipulation of such complex objects is considerably more challenging than unconstrained reaching or rigid object manipulation and is likely to require different control models.

The few existing studies on non-rigid object manipulation aimed to identify the objective functions that humans optimize [4], [5]. However, they all examined linear mass-spring systems which do not have the considerably more complex nonlinear dynamics of the broad range of objects that humans interact with on a daily basis. Moreover, these models do not provide insight about how they are generated by a controller, hence remain descriptive. Further, online solutions of such optimization problems combined with the inverse dynamics computation to generate the planned/desired trajectories would be a daunting task for human brains.

We hypothesized that humans simplify the control of physical interaction with dynamically complex objects by using dynamic primitives: submovements for discrete actions, oscillations for rhythmic actions, and mechanical impedance for physical interaction with objects [6]. To test this hypothesis, we designed an experiment in which participants were instructed to transport a simplified, yet nonlinear and underactuated model of a cup of coffee in a virtual environment. Participants were instructed to move the cup from a start to a target position such that the ball comes to a full rest. 'Zeroing out' terminal oscillations of the ball presents a major challenge for the operator. To avoid trivial slow solutions, a metronome specified a relatively fast movement duration, which also allow comparison with the predictions from the different models. As shown in the control literature, this 'no-terminal-oscillation' task afforded a simple solution, known as input shaping [7]. However, as the experimental results revealed, neither the optimization models, nor the input shaping could replicate the human data. Instead, a controller using submovements in the feedforward command coupled with hand impedance better approximated the human trajectories. This model is an example how dynamic primitives may simplify control [6].

II. The Cup-and-Ball Experiment

For the virtual implementation, the cup of coffee was reduced to a 2-dimensional semicircular arc with a heavy ball rolling inside, representing the sloshing coffee. The ball's motion was modeled by a pendulum suspended from a cart; the arc of the cup corresponded to the ball's semicircular path (Fig.1). The motion of this 2D cup was limited to the horizontal axis only. The experimental trials were collected in two blocks of 50 trials each. Subjects were instructed to both minimize terminal oscillations and meet the timing constraints of $1.4\ s$ and $1.2\ s$, respectively. These timing constraints were fast as the candidate models generated different predictions only for such fast movements. At the end of every trial subjects received feedback about their timing error in the form of a change in ball color. In addition, the value of the maximum terminal ball angle was shown on the screen.

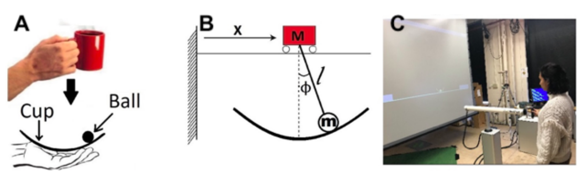

Fig. 1. **A.** Real task. **B.** Mechanical model. **C.** Virtual environment.

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III. Candidate Models

1) Optimization-based models: Two models proposed previously for complex object control postulate that humans seek to optimize a smoothness criterion of the object and/or hand kinematics: minimum crackle of the object (MCO) [4] and dynamically constrained minimum jerk of the hand (DCMJH) [5]. For the cup-and-ball task, these models predicted that cup velocity profiles would contain two symmetric peaks and the velocity minimum between the peaks would become more negative for faster movements. These two predictions were tested with human data.

2) Submovement-based models: This second category of models assumes that humans use dynamic primitives, specifically submovements in their forward control path and impedance for the interaction. More specifically, for this task the submovements are used in an input shaping strategy. Input shaping is a command generation strategy for rapidly moving flexible systems with low levels of vibration. Control is achieved by convolution of a motion profile with impulses of specific amplitude and timing [7]. Several variants of this model were explored: with and without impedance, and with and without a feedforward force input term, with and without variability in the impulse timing as computed by input shaping, to reflect imperfections in human execution. Lastly, extending the model with impedance increased the system to have two modes, potentially increasing rather than simplifying the control challenge. Therefore, we also tested a model that generated impulses only from a single mode by simplifying the cup-and-ball to a lumped rigid mass. This represents the case where humans use hand impedance but generate a trajectory based on the object's mass without knowledge of its dynamics.

IV. Results

A. Data Analysis

Data analysis revealed two findings that opposed the predictions of the optimization-based models:

1) The velocity peaks were consistently asymmetric; the first peak was significantly larger than the second (Fig.2A).
2) The minimum velocity between the two peaks did not decrease at faster movement durations (Fig.2B).

B. Model Fitting

As the experimental results did not support the two predictions, the optimization models were rejected as plausible models for human control. In contrast, the submovement-based models that included hand impedance could reproduce the asymmetric peaks in the cup velocity. A nonlinear optimization was used to find the parameters that minimized the root mean squared error (RMSE) between experimental and simulated hand trajectories for the different models. A meta-analysis compared model variations that differed only in one parameter. Simulations with feedforward force input (FFF) and impulse timing variability (T-Variability) fit the subject data better than those without feedforward force or timing variability (Fig.3A). Models using single-mode input shaping performed marginally better than those with inputs shaped using both

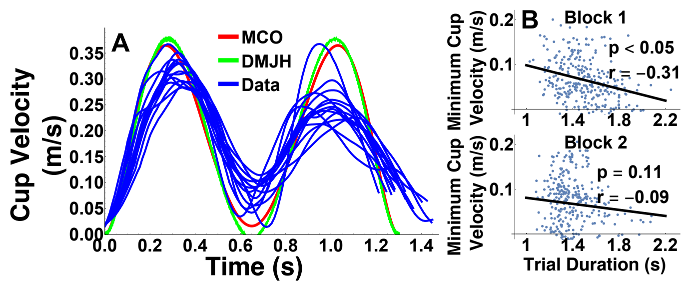

Fig. 2. **A.** Optimization-based model predictions and experimental data. **B.** No correlation between minimum velocity and movement duration.

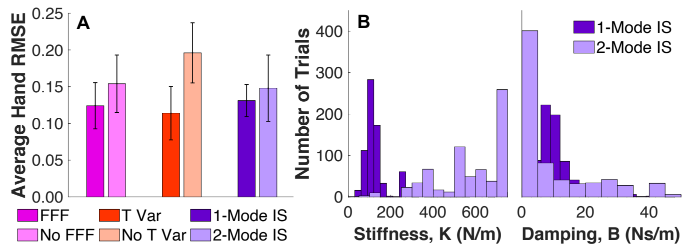

Fig. 3. **A.** Mean RMSE values across different models. **B.** Histograms of best-fit hand impedance values for single- vs. multi-mode input shaping.

modes. The latter result suggests that humans do not need exact knowledge of object dynamics beyond its total mass. The optimal stiffness values for single-mode simulations were closer to those typically observed for the upper limb than the multi-mode values (Fig.3B). The best-fit model was one that included a feedforward force, timing variability with single-mode input shaping control.

In conclusion, these results suggest that humans do not use optimization strategies but rather simplify their control of complex objects by using dynamic primitives, specifically by composing submovements and hand impedance.

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