

Transient Behavior and Predictability in Manipulating Complex Objects

Rashida Nayeem, Salah Bazzi, Neville Hogan, and Dagmar Sternad

Abstract— Relatively little work in human and robot control has examined the control of underactuated objects with internal dynamics, such as transporting a cup of coffee, a task that presents little problems for humans. This study examined how humans move a ‘cup of coffee’ with a view to identify principles that may be useful for robot control. The specific focus was on how humans choose initial conditions to safely reach a steady state. We hypothesized that subjects choose initial conditions that minimized the transient duration to reach the steady state faster, as it presented more predictable dynamics. In the experiment, the cup of coffee was reduced to a 2-D cup with a sliding ball inside which was simulated in a virtual environment. Human subjects interacted with this virtual object via a robotic manipulandum that provided haptic feedback. Participants moved the cup between two targets without losing the ball; they were instructed to explore different initial conditions before initiating the continuous interaction. Results showed that subjects converged to a small set of initial conditions that decreased their transient durations and achieved a predictable steady state faster. Simulations with a simple feedforward controller and inverse dynamics calculations confirmed that these initial conditions indeed led to shorter transients and less complex interaction forces. These results may inform robot control of objects with internal dynamics where the effects of initial conditions need further investigation.

I. INTRODUCTION

Humans are exquisitely adept at using tools and interacting with dynamically complex objects. Tool use ranges from simply using a fork to eat to highly involved actions, such as cracking a whip. A seemingly mundane example of physically interacting with an object with internal dynamics or ‘complex object’ is transporting a cup of coffee: when a person moves the cup, the cup enacts a force on the coffee. The coffee then applies forces back on the cup and then the hand. Despite these nonlinear interaction forces, humans are extremely skilled at such tasks, which is surprising considering the delays in their neural transmission rates and noise in their systems [1]–[5]. Better understanding of how humans manage complex objects with such dexterity may be instructive for robotic control and manipulation [6].

The most frequently studied task in robotic manipulation is the pick-and-place paradigm, and much of this research has been confined to rigid objects [7]. Manipulating flexible or underactuated objects presents significant challenges: successful control would require models of deformation and

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complex interaction forces, which require daunting computations for both humans and robots [8]. Moreover, robotic manipulation has focused on the pre-contact stage, i.e., on planning the grasp, rather than the subsequent interaction. At most, goal-directed object manipulation is limited to moving the object to another position [9]. Goal-directed tool use with continuous physical interaction has received relatively little attention to date.

Current approaches in robotic control and motion generation have predominantly focused on steady-state behavior and stability. However, when initiating an action from a steady state, the system inevitably starts from initial conditions and passes through a transient state, which may be unstable. The transient state, between steady states, remains to be thoroughly investigated. Nevertheless, further study of transient dynamics would be of great use to the field of robotics [10]–[12]. Since stability is critical for robot controllers, the approach has been to build locally stabilizing control policies that eliminate the effect of initial conditions *i.e.*, funneling initial conditions into the desired behavior [13] [14]. These control policies effectively create basins of attraction that span the entire state space. However, it is also possible to control a dynamical system by appropriately setting its initial conditions.

Recent studies in motor neuroscience have provided some evidence that the brain generates movements by setting appropriate initial conditions [15] [16]. Specifically, the neural networks in the brain responsible for movement execution behave as dynamical systems that are initialized with a desired state and then driven into patterns of collective activity [17]. In this spirit, Ernesti et al. generated a control policy for a humanoid robot wiping a windshield that selected initial conditions to tune transient behaviors using dynamic motion primitives [18]. The present study examined how humans start movements and whether they chose appropriate initial conditions to set up predictable interactions.

Transient dynamics can create unpredictable interaction forces; mastering this start-up transient to reach a desired steady state is not trivial. The human motor system faces significant limitations in its ‘hardware’: transmission speed peaks at ≈ 100 m/s and bandwidth in the human muscular response rarely exceeds 5 Hz [19]. The human neuromotor system can be variable and noisy, with an accuracy in timing of around 9 ms [19]–[21]. These features challenge the use of feedback control in continuous physical interaction because loop times are not fast enough for adaptation and error corrections [22] [23]. We hypothesize that humans deal with these shortcomings in the neuromotor system by making interactions with objects predictable.

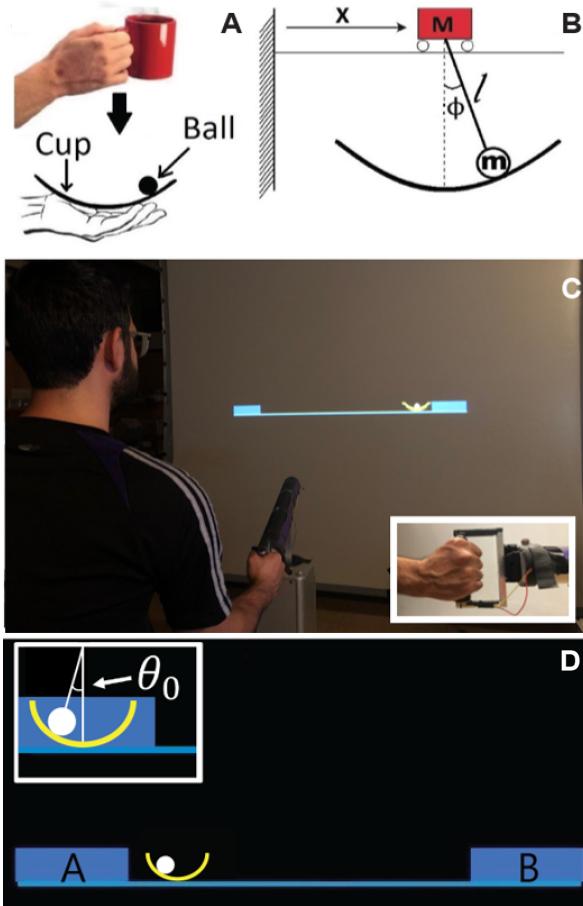


Fig. 1. (A) The task was inspired by transporting a cup of coffee, simplified to a cup with a ball sliding inside. (B) Mechanical model of cart-pendulum system. (C) A participant holds the HapticMaster handle to move the cup while viewing the corresponding graphics on a projection screen. The inset shows the subject's grip the robot handle. (D) Screen display. The inset shows the definition of the ball angle, the ball at rest at the bottom of the cup was considered 0 deg, clockwise direction from the bottom was defined as a negative angle.

Previous work in our lab showed that in continuous rhythmic interactions, subjects selected hand impedance values that increased predictability of the object dynamics, even though this required increased mechanical effort [24]. However, in the previous studies, initial conditions of the object were fixed, and the analysis only focused on steady state behavior [25]. The present study aimed to answer the following question: when given the option to choose them, do humans explore and exploit initial conditions? We investigated how humans physically interact with a non-rigid object, transporting a ‘cup of coffee’ in a continuous rhythmic manner. Three specific hypotheses were tested: 1) Subjects will converge to a subset of all possible initial conditions. 2) Subjects will shorten their transient duration. 3) Subjects will maximize the predictability of the task dynamics. Results from the human experiments were compared with results from two simulations of the cart-and-pendulum system: inverse dynamics control and forward simulations using a coupled model with hand dynamics. These findings may inform new control strategies for robotic manipulation of complex objects.

II. METHODS

A. Mechanical Model

A cup of coffee is underactuated since the coffee motion is coupled to motion of the cup and cannot be controlled directly. For the virtual rendering, the real task was simplified to a two-dimensional semi-circular cup with a ball inside, displayed on a large projection screen (2.4x 2.4 m) (Fig.1C). This simplification maintained the essential features of this task: physical interaction, underactuation, and nonlinearity [26]–[28]. The semi-circular cup was confined to moving on a horizontal line with a ball sliding inside. Under the premise that the ball was sliding and not rolling, the system was mathematically equivalent to the model of a cart moving on a line with a suspended pendulum. The ball represented a weight at the end of the pendulum and the cup position on the horizontal axis was equal to the cart position. The arc of the cup outlined the rotational path of the pendulum, where the clockwise direction was defined as negative (Fig.1). Subjects moved the cup-and-ball system solely in the horizontal direction, using a robotic manipulandum. The robot transmitted the force of the ball acting on the cup to the subject. The equations of motion are described as the following:

$$(m_c + m_p)\ddot{X} = m_p d[\dot{\theta}^2 \sin \theta - \ddot{\theta} \cos \theta] + F_{inter} \quad (1)$$

$$m_p d[\dot{\theta}^2 \sin \theta - \ddot{\theta} \cos \theta] = F_{ball} \quad (2)$$

$$\ddot{\theta} = -\frac{\ddot{X}}{l} \cos \theta - \frac{g}{l} \sin \theta \quad (3)$$

F_{inter} is the force of the human hand interacting with the cart. X and θ denote the cart position and the pendulum angle respectively. F_{ball} is the force of the pendulum (ball) on the cup. Parameters of the system were: cart mass $m_c = 2.40$ kg, pendulum mass $m_p = 0.60$ kg, pendulum length $l = 0.45$ m, and gravitational acceleration g . The values were selected so that the masses were light enough to avoid fatigue, but heavy enough such that subjects experienced F_{ball} .

B. Apparatus and Data Acquisition

During the experiment session, participants sat on a chair approximately 2 m in front of the screen and held the handle on a 3-DOF robotic manipulandum capable of haptic feedback (Fig.1C). The motion of the robotic manipulandum was limited to horizontal direction to guarantee that the mathematical model and the virtual system had the same dimension of motion. The force of the participant's hand interacting with the robotic handle, F_{inter} , controlled the position of the virtual cup X along a horizontal line [25], [29]. When interacting with the handle, participants could experience the system inertia and F_{ball} acting on their hand from the haptic feedback provided by the robot [29]. The ball kinematics, virtual display and haptic feedback were implemented using a custom-written C++ program that was created based upon the HapticAPI (Moog FCS Control Systems). The visual display showed two blue rectangular

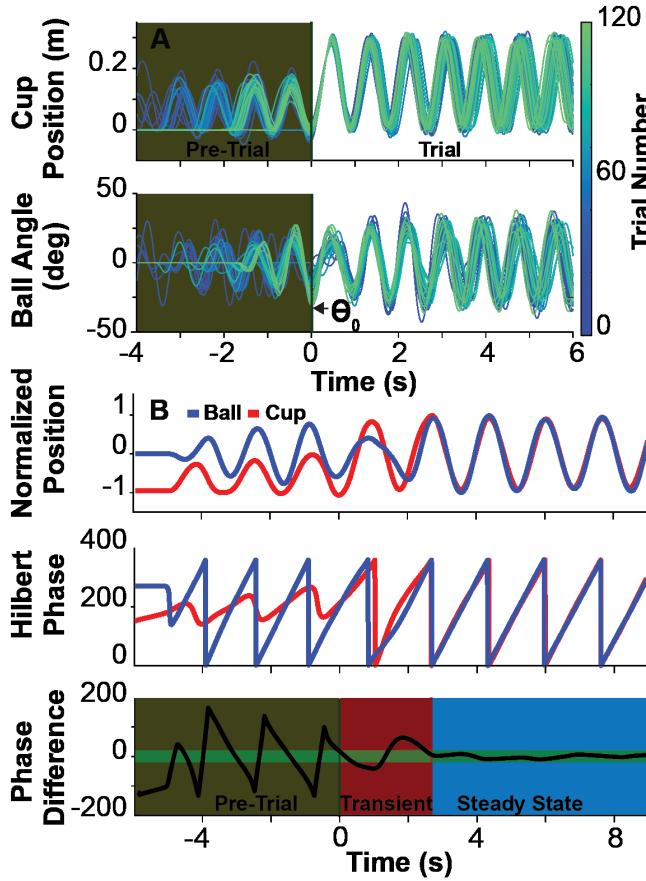


Fig. 2. (A) Time series of cup position and ball angle of a 120 trials of one subject aligned by the moment of initiation. (B) Method for transient calculation on one trial of one subject: based on cup and ball position continuous Hilbert phase was calculated. The difference between cup phase and ball phase was used to determine the beginning of the steady state of the trial.

targets directly above a horizontal line which corresponded to the desired peak-to-peak displacement of the cup. A yellow semi-circular arc depicted the cup and the ball was visualized as a white circle (Fig.1 D). The ball would escape from the cup if the ball angle exceeded ± 50 deg. The actual displacement of the handle was 4 times smaller than the visual displacement of the cup on the screen. The cup model simulation was 7.5 times larger than the cup in the virtual display. These parameters were chosen such that the visuomotor gain was as close to 1:1 as possible so that it would not stretch the perception of realism. The cup kinematics, the interaction force F_{inter} , and the computed ball kinematics were recorded at 60 Hz.

C. Experimental Task

At the start of the trial, the cup was in the center of Box A with the ball at the bottom of the cup (0 deg) (Fig.1). Prior to starting the rhythmic task, subjects were encouraged to explore the best initial conditions by ‘jiggling’ the cup back and forth for as long as they wanted; this was called the ‘Pre-Trial’ interval (Fig.2A). Once they felt ready to start the trial they moved the cup towards Box B and continued moving in rhythmic fashion between the two boxes without losing the ball ($|\theta| < 50$ deg). A metronome started when

the participant first reached Box B and continued to pace their movements at 0.6 Hz for 15 s. The distance between the centers of Box A and Box B was 0.3 m. Importantly, subjects were not explicitly told to shorten their transient duration. The experiment was divided into 4 sets of 30 trials each, for a total of 120 trials. 13 right handed college-age adults volunteered for the experiment (8 male). All subjects gave written informed consent, approved by the Northeastern University Institutional Review Board, prior to the experimental session.

III. DATA ANALYSIS

The variables that tested the hypotheses were initial ball angle, transient duration and predictability of the trial segment.

1) *Initial Ball Angles (θ_0)*: Initial conditions of the cup and ball were defined at the time when the cup position was at its left-most excursion (a local maximum) before subjects started the continuous rhythmic movements (Fig.2A). All movements prior to that moment were considered the ‘Pre-Trial’ interval and movements after that time point were considered to be in the trial. The most important variable was the ball angle at the start of the trial, θ_0 . Cup velocity at this local maximum of cup position was zero by definition; ball velocity and cup position were evaluated, but proved to be small and have minimal effect on the subsequent trial, both in simulation and experiment.

2) *Transient Duration*: To calculate the duration of the transient, a criterion for steady state first had to be determined [30]. For the movement frequency of 0.6 Hz, mathematical analysis showed that the ball and cup position were in-phase (i.e. had zero phase difference) at steady state. To identify when the transient trajectories approached steady state, the instantaneous phase differences between cup and ball position were computed using the Hilbert transform (Fig.2B) [31]. Since human trajectories are prone to variability, a threshold had to be set to define the onset of relative zero phase difference between cup and ball. This threshold was ± 27 deg (± 15 percent of 180 deg). The time point when the phase difference entered and remained within this threshold defined the end of the transient and start of the steady state (bottom panel of Fig.2B).

3) *Mutual Information*: Predictability was mathematically operationalized by mutual information (MI) between the input and output of the system. High MI indicates a high degree of certainty [32]. Unlike cross correlation, MI assesses both linear and nonlinear dependencies [33] [34]. In the context of this study, MI quantified how much the cart trajectory predicted the interaction force. The cart trajectory was defined by its phase in state space, $\phi(t) = \arctan \left[\frac{\dot{X}}{(2\pi f)X} \right]$. $F_{inter}(t)$ was defined above. MI was computed using the following formula:

$$MI(\phi, F_{inter}) = \iint P(\phi, F_{inter}) \ln \left[\frac{P(\phi, F_{inter})}{P(\phi)P(F_{inter})} \right] d\phi dF \quad (4)$$

P represents the probability density functions for $\phi(t)$ and $F_{inter}(t)$, which were approximated via a linear interpolation of nonlinear Gaussian smoothing kernels [32], [35]. MI was calculated from the beginning to the end of the trial. It is a dimensionless quantity and is displayed on a natural log scale (nat).

IV. RESULTS

A. Experimental Results

Maintaining the target frequency of 0.6 Hz was challenging for subjects; the average frequency attained was 0.58 Hz with a range of 0.55 Hz to 0.63 Hz. Note that 2 of 13 subjects had more than 40 percent failures, i.e. they lost the ball, and were excluded from analysis. The percentage of failed trials across the remaining subjects was 16.7 percent and their average peak-to-peak amplitude was 0.308 m.

1) *Initial Ball Angles (θ_0)*: The average initial ball angles across subjects changed from -9.69 deg in the first 5 trials (standard deviation 9.94 deg) to an average of -22.28 deg in the last 5 trials (standard deviation 10.59 deg). This change was statistically significant ($p = .0066$). Fig.3A shows the gradual change of ball angles across subjects that seemed to converge and reach an asymptote after about 60 trials. Subjects converged to a preferred initial condition, a result that supported Hypothesis 1. The two other variables at initiation, cup position and ball velocity, were negligible: the mean X_0 was $-0.157 \pm .019$ m (the centers of Box A and Box B were located at -0.15 m and 0.15 m respectively) and the mean $\dot{\theta}_0$ was $-15.12 \text{ deg/s} \pm 31.65 \text{ deg/s}$.

2) *Transient Duration*: The transient duration decreased over the 120 trials, supporting Hypothesis 2 (Fig.3B). In the first 5 trials, transient duration was on average 8.02 s (standard deviation 4.85 s), decreasing to an average of 3.67 s (standard deviation 3.10 s) in the last 5 trials. This significant decrease ($p = 0.0024$) showed that subjects reduced the transient duration, although this was not an explicit goal of the task.

3) *Mutual Information*: The MI between $\phi(t)$ and $F_{inter}(t)$ increased from 1.137 nat in the first 5 trials to 1.385 nat in the last 5 trials (Fig.3C). A t-test confirmed the statistical significance of this change ($p = 6.850e^{-05}$). Participants implicitly raised the predictability of their interaction forces with the system, which supported Hypothesis 3.

B. Simulation Results and Hypothesis Testing

To further understand the subjects' choice of initial conditions given the known dynamics of the complex object, inverse dynamic and forward dynamic simulations were conducted. In the simulations, initial ball velocity was $\dot{\theta}_0 = 0 \text{ deg/s}$, and it was found that varying $\dot{\theta}_0$ did not make a significant impact upon the simulation results.

1) *Effect of initial conditions on interaction force*: Inverse dynamics calculations were conducted for different initial ball angles (θ_0) to determine what interaction force, $F_{inter}(t)$, was needed to obtain the instructed sinusoidal cup displacement with frequency f , peak-to-peak amplitude A , and time t : $X(t) = (A/2)\sin(2\pi ft + \pi/2)$. In this case

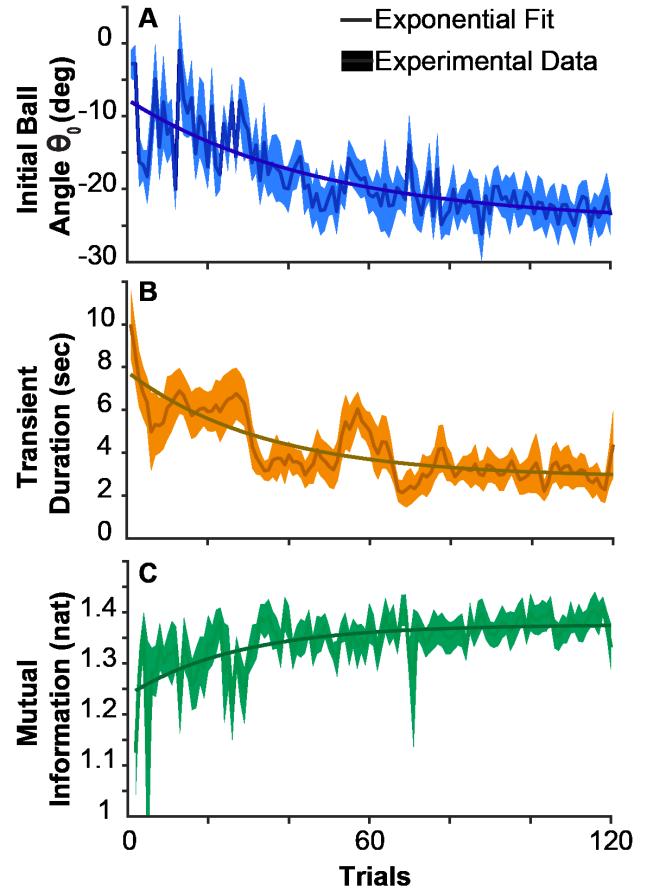


Fig. 3. (A) Initial ball angle averaged across subjects over trials with an exponential fit of the form $Ae^{-\frac{t}{\tau}} + B$, $\tau = 48.13$, $R^2 = 0.65$. (B) Transient durations averaged across subjects over trials with an exponential fit of the form $Ae^{-\frac{t}{\tau}} + B$, $\tau = 34.03$, $R^2 = 0.68$. (C) MI averaged across subjects over trials on a natural log scale with an exponential fit of the form $A(1 - e^{-\frac{t}{\tau}}) + B$, $\tau = 27.22$, $R^2 = 0.44$. In all three panels the shaded bands around the experimental mean denote one standard error.

$f = 0.58$, the subjects' mean frequency, and $A = 0.3$ m. This analysis did not infer a specific controller; instead it calculated the $F_{inter}(t)$ required to generate the instructed kinematic output using Eq. 1. Although $X(t)$ and $\dot{X}(t)$ were sinusoids, the kinematics of the ball $\theta(t)$ and $\dot{\theta}(t)$ were not necessarily sinusoidal. The form of the $F_{inter}(t)$ profile was reliant upon the values of θ_0 and $\dot{\theta}_0$. Fig.4 (A,B) displays two example profiles produced with two different θ_0 that produced the same sinusoidal cup trajectories $X(t)$, but with different initial ball angles. $F_{inter}(t)$, generated with $\theta_0 \approx 45.8$ deg, rendered a profile that looks irregular and has a relatively large range of forces (Fig.4B). In contrast, the left $F_{inter}(t)$ profile using $\theta_0 \approx -28.4$ deg (Fig.4A) resulted in a completely predictable oscillatory force profile.

To convey the behavior of $F_{inter}(t)$, the force profile $F_{inter}(t)$ was strobbed at the maxima of the periodic cup profile for a given θ_0 . The strobbed force values were plotted on the force-axis to produce a marginal distribution against the given θ_0 . This analysis was repeated for every θ_0 in Fig.4C. This produced a distribution resembling a bifurcation diagram for a period-doubling route to chaos in nonlinear systems [36] [37]. The evolution of complex behavior from

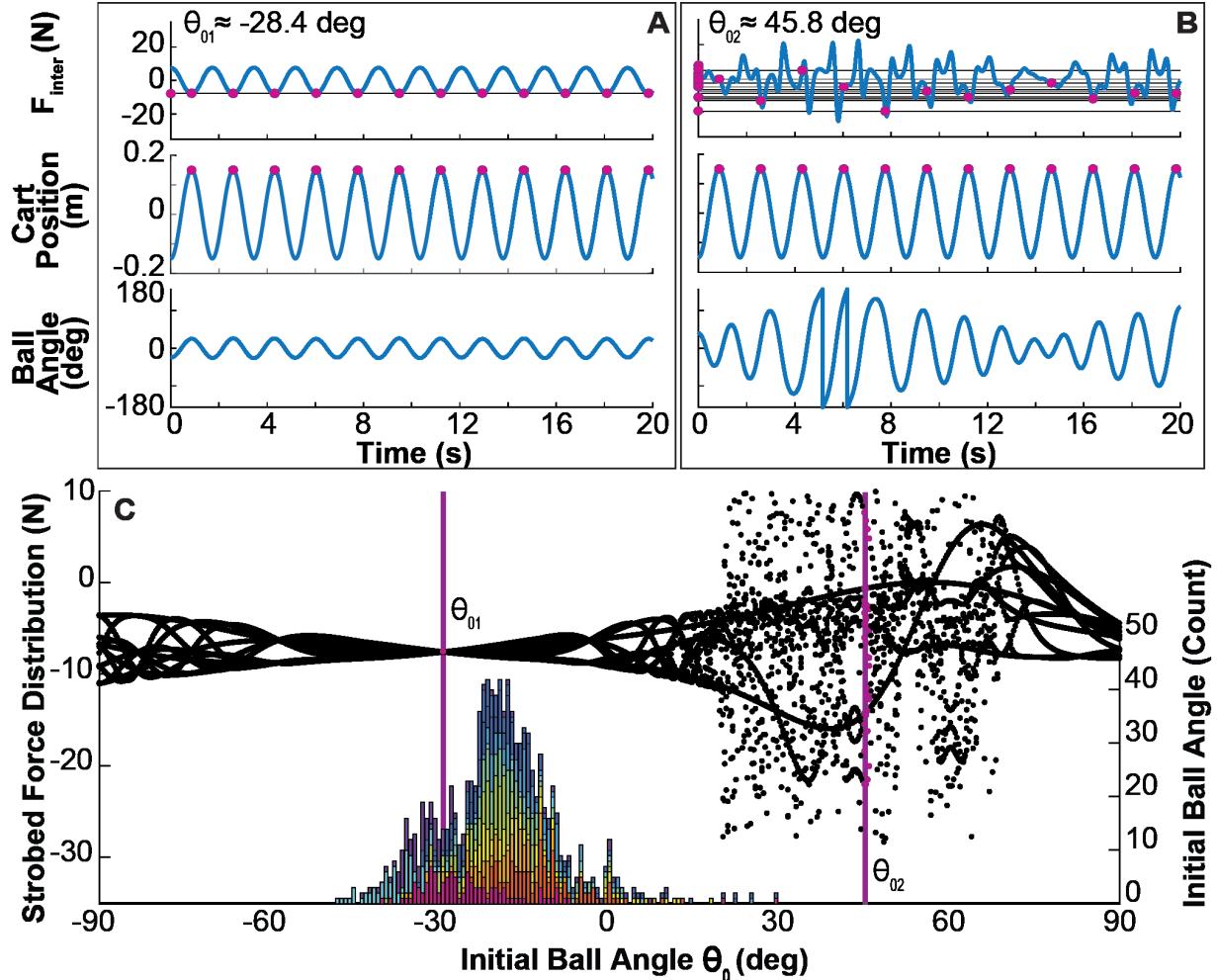


Fig. 4. (A) Example profile of a subject's interaction force $F_{\text{inter}}(t)$, cart position $X(t)$, and ball angle $\theta(t)$, for rhythmic cup displacement starting with $\theta_0 \approx -28.4$ deg; cup frequency and amplitude were 0.58 Hz and 0.3 m (peak-to-peak). At every maximum of $X(t)$, the value of F_{inter} was determined, as indicated by the magenta points at each peak of $X(t)$. The strobed force values were mapped onto the vertical force axis to obtain the marginal distribution (shown by the magenta point on the y-axis). The marginal distribution of this profile is a single point due to the periodic profile. These distributions were obtained for each simulation with different θ_0 . (B) Example profile of interaction force $F_{\text{inter}}(t)$, cart position $X(t)$, and ball angle $\theta(t)$, for a trial initiated with $\theta_0 \approx 45.8$ deg; cup frequency and amplitude were 0.58 Hz and 0.3 m (peak-to-peak). The strobed force values render a marginal distribution of a wider range due to the irregular $F_{\text{inter}}(t)$ as seen by the magenta points on the y-axis. (C) Marginal distributions of strobed forces for all initial ball angles, θ_0 , calculated from inverse dynamics simulations, shown in black (left y-axis). The distributions for $\theta_{01} \approx -28.4$ deg and $\theta_{02} \approx 45.8$ deg are in magenta. The figure also includes a histogram of θ_0 for all experimental trials pooled over all subjects; different subjects appear in unique colors (right y-axis). The peak of the histogram aligns with initial ball angles that render the low variability in the strobed forces.

simple dynamics has been extensively examined in research on nonlinear dynamics [38]–[41]. This analysis found that the most predictable input force profile was at $\theta_0 \approx -28.4$ deg. To illustrate how subjects' preferred initial angles, θ_0 , compared to those predicted by inverse dynamics, the bottom of Fig. 4C includes a histogram of θ_0 for all trials pooled over all subjects (different subjects appear in different colors). The initial angles subjects most frequently chose aligned with θ_0 values that produced the least complex force patterns $F_{\text{inter}}(t)$ in the inverse dynamics simulation. This provided support for Hypothesis 3 that subjects chose initial conditions that favored simple interaction forces with more predictable dynamics.

2) *Effect of initial conditions on transient duration:* To derive predictions about transient duration, forward dynamics simulations were performed. The cup-and-ball system was

connected to a model of hand impedance (Fig. 5) [24]. The hand interactive dynamics were represented by a spring K , in parallel with a damper B . The desired trajectory was expressed as $X_{\text{des}}(t)$, $\dot{X}_{\text{des}}(t)$, which are the sinusoids that describe cup displacement and velocity for the appropriate frequency and amplitude of the cup displacement: $X_{\text{des}}(t) = (A/2)\sin(2\pi ft + \pi/2)$. In the experiment, the actual cart trajectory $X(t)$ differed from $X_{\text{des}}(t)$, most likely due to the ball force functioning as a perturbation. The hand impedance functioned as a simple proportional derivative controller and aided in minimizing the effects of this perturbation [24]. The equations of motion of this coupled model are:

$$(m_c + m_p)\ddot{X} = m_p d[\dot{\theta}^2 \sin \theta - \ddot{\theta} \cos \theta] + F_{\text{inter}} \quad (5)$$

$$\ddot{\theta} = -\frac{\ddot{X}}{l} \cos \theta - \frac{g}{l} \sin \theta \quad (6)$$

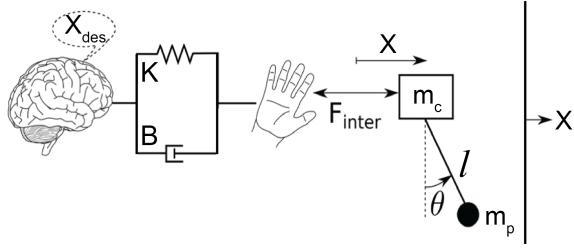


Fig. 5. The forward model with simple hand impedance coupled to the cart-pendulum-system. The interactive dynamics are represented by a spring K in parallel with a damper B . The desired trajectory is denoted as $X_{des}(t)$.

$$F_{inter} = -K(X - X_{des}) - B(\dot{X} - \dot{X}_{des}) \quad (7)$$

K and B were considered constant during a trial. To obtain an estimate for these two parameters from the experimental data, an optimization procedure identified the values of K and B that best approximated the experimental cup and ball trajectories for each trial of each subject. The simulated f and A were matched to the exact frequency and amplitude for the particular trial. The objective function C was the root mean square difference between all kinematic traces over the entire trial, for more detail, refer to the work by Maurice et al. [24].

To predict transient durations for different initial conditions, this model was forward simulated for different initial conditions. As the calculations proved to be sensitive to cup frequency, they were performed for a range of frequencies observed in the experimental data. The cup amplitude was set to the average experimentally observed value of 0.3 m. The results also varied with different stiffness and damping values; hence, calculations were performed for a range of K and B values estimated from the experimental data. Sweeping through all these parameters within the range of subjects' observed behavior, the transient duration was calculated for each simulation run. The same analysis procedures applied on the experimental data were used to obtain the transient durations for the simulated data. Fig. 6 summarizes the transient durations for the relevant frequencies and initial ball angles for $K = 40$ N/m and $B = 50$ Ns/m. These stiffness and damping values were the modes in the estimates from the subject data. The dark blue color represents the areas that predicted the shortest transient durations.

To compare simulation and experiment, individual subjects' trials were superimposed (red points). Only subject trials that had estimated stiffness and damping in the range of $K = 40 \pm 10$ N/m and $B = 50 \pm 20$ Ns/m were included. The figure shows trials in which the optimization-based determination for the impedance parameters were highly reliable ($C \leq .10$). Comparing the data with respect to the simulated predictions shows that subjects chose initial conditions that coincided with those in the model that produced the shortest transient durations. These results provided further support for Hypotheses 1, 2 and 3. Subjects preferred initial conditions that shortened the transients and reached a predictable steady state faster.

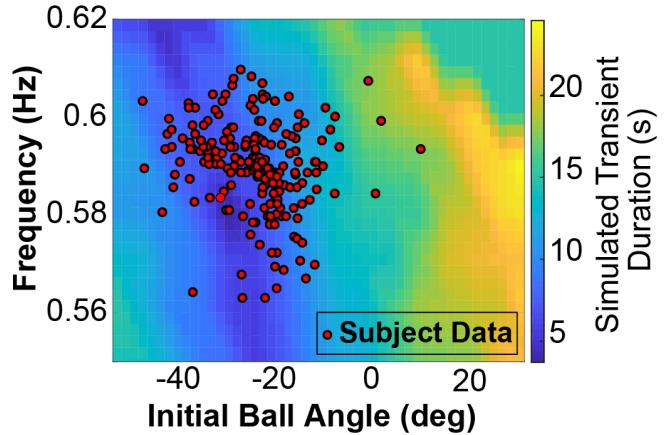


Fig. 6. Transient durations for different frequency and initial ball angles simulated with the forward simulation using $K = 40$ N/m and $B = 50$ Ns/m. Subject trials with estimated stiffness and damping in the range of $K = 40 \pm 10$ N/m and $B = 50 \pm 20$ Ns/m are superimposed.

V. DISCUSSION AND CONCLUSIONS

This study investigated strategies that humans adopt when manipulating objects with underactuated dynamics. It showed that, when given a choice, subjects chose initial conditions that decreased their transients and reached a predictable steady state faster. Subjects chose initial ball angles that were associated with less complex interaction forces, demonstrating that subjects preferred predictable interaction forces. Mutual information (MI) increased over trials demonstrating that subjects interacted with the cup and ball in an increasingly predictable manner. The initial ball angles and frequencies that subjects chose matched initial ball angles and frequencies that decreased their transient duration in a forward simulation using impedance control. These results are the first support for the hypothesis that humans can identify initial conditions which minimize transients and favor reaching a steady state faster, enhancing predictability.

The results presented here may inspire new control strategies for robotic manipulation: strategies that exploit initial conditions instead of trying to cancel their effects. The notion of controlling a system by making small changes to its parameters has been explored for systems with chaotic dynamics. For example, Ott, Grebogi, and York used small perturbations to system parameters to attain stable behavior, rather than actively changing the system's dynamics [42], [43]. One could abstract these 'accessible system parameters' to be the initial conditions of the system; control of a system is thus achieved by setting its initial conditions.

Based on these results and those from our earlier work, we propose a new guiding principle for robot control: exploit initial conditions to maximize predictability. It has been shown in previous work that human-robot interaction is augmented when human movement characteristics are considered in robotic control [44]. The findings from this present work provide insight on how to facilitate object interaction, especially physical interaction and collaboration with humans. As human-robot interaction becomes more widespread, further investigation into human motor control schemes will be crucial.

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