Visual and haptic feedback enable on-line tuning to resonant dynamics.

Felix Huang, R. Brent Gillespie, Arthur D. Kuo

Abstract—We conducted two experiments to determine what sensory feedback is required in a motor task where subjects manually excite oscillations of a virtual spring and inertia object. We examined performance considering the frequency content of the manual input, the consistency of phasing behavior between input and output motion, and the effective work rate by human subjects on the spring-inertia system. In Experiment-1, subjects (n=11) performed the manipulation task at a fixed resonant frequency ($\omega_r = 7$ rad/s) with and without augmented sensory information, using only haptic feedback as the candidate channel. Including feedback resulted in superior performance in each metric (paired t-tests: p < .05). In Experiment-2, subjects (n=10) performed a similar task, with the additional challenge that various resonant frequencies were presented without preview ($\omega_r = 7, 9, 11, 13$ rad/s) under three feedback conditions: vision, haptic, or vision and haptic combined. Combined feedback demonstrated superior performance according to phase marker variability and effective work rate (paired t-tests: p < .05) in one case for $\omega_r = 7$ rad/s. Our results demonstrate that a feedforward strategy is insufficient for maintaining resonant behavior of a spring-inertia system, while sensory feedback from vision or haptic sources allows the necessary on-line corrections and even rapid tuning to changes in the resonant frequency to occur.

Index Terms—internal model, upper extremity, manual control, motor control, motor adaptation.

I. INTRODUCTION

Humans often perform motor tasks that require interacting with extrinsic objects. The simple act of picking up a rock or stick and throwing it requires a sense of the object’s mass or other properties, often gained despite little prior experience with that particular object. Even more challenging are tasks where objects are neither rigidly attached to nor directly grasped by the body. For example, when bouncing a ball, pushing a child’s swing, or casting a fishing line, there are certain degrees of freedom that are underactuated (Lynch and Mason, 1996; Piccoli, 2005), that is, they are extrinsic to the body and can only be actuated indirectly or intermittently (Lynch and Black 2001). Moreover, these degrees of freedom are typically influenced by harnessing the resonant dynamics of the task. Despite these complexities, humans routinely interface with objects of varying size, shape, and form (Burton, 1990). Prior experience with similar objects almost certainly contributes to dexterity (Chan T.C, 1995). However, motor control also appears to be fine-tuned according to a particular object’s unique dynamics. Both learning from experience and fine tuning depend on feedback.

Motor tasks can benefit from feedback in multiple ways. In reaching and other tasks that rely heavily on feedforward control, feedback is used to adjust the motor pattern to be applied in subsequent movements (Fig. 1a). The central nervous system may be interpreted as using an internal model to effectively invert the dynamics of a task (Kawato, 1999; Franklin, 2003), yielding the motor pattern that achieves the desired path or target. With practice, humans adapt reaching motor patterns to compensate for a variety of novel external force fields or alterations to limb dynamics (Shadmehr and Mussa-Ivaldo, 1994). The internal model is not limited to body dynamics alone. For example, humans learn motor patterns for interacting with an extrinsic mass through a spring (Dingwell et al., 2002). This necessitates inverting the dynamics of both the limb and the mass-spring system. Visual, proprioceptive, and haptic feedback all contribute to learning of appropriate motor patterns.

Feedback can also be used on-line (Fig. 1b), to adjust a movement as it is occurring (Johansson, 1998; Kuo A.D., 2002). There is a component of on-line feedback even in reaching, to produce in-flight corrections that improve accuracy (Wang, 2001; Takahashi, 2001; Mah C.D., 2001; Burdet 2001). As with feedback for learning and adaptation, on-
line feedback also benefits from multiple channels of sensory information (Gharamani, 1997). For example, humans can easily bounce a tennis ball on a racquet with visual and proprioceptive feedback alone, but their steadiness improves with haptic feedback of the ball-racquet collision (Sternad, 2001). This feedback is helpful even though humans adopt a stable bouncing strategy (Schaal, 1996), presumably because haptic feedback provides a clear timing signal. On-line feedback is especially critical when the central nervous system must stabilize inherently unstable tasks. It is impossible to balance an inverted pendulum mounted on a moveable cart (Mah and Mussa-Ivaldi, 2003), or a ball rolling on beam pivoted about a horizontal axis without feedback (Huang et al., 2005 in press). Feedback is employed not only on-line, but also off-line to adjust the on-line feedback control program as it is being practiced and learned. Visual and proprioceptive feedback can be sufficient, but the addition of haptic feedback appears to improve learning and control (Sternad, 2001a).

There may be yet another use for feedback, one that applies to relatively familiar, rather than novel, tasks (Conditt, 1997). Humans regularly interact with extrinsic objects that have common dynamics but perhaps differing parameter values (e.g., pen, paperweight, mug). Instead of a specific motor program for each object, the CNS may have a general motor program that requires only minor fine tuning to account for the particular object’s parameters. In these cases, it may be necessary only to calibrate or identify parameters for a pre-existing internal model (Fig. 1c). This calibration need not be confined to inertial properties (Turvey, 1999; Kreifeldt, 1979; Solomon, 1989), nor need it occur separately from control of the object. The examples first named above—bouncing a basketball, pushing a swing, or casting a fishing line—require interacting with a resonant system, where extensive prior experience may have yielded considerable familiarity. However, calibration of control may depend on system parameters such as stiffness or resonant frequency, with the requisite identification occurring during the movements themselves. As with other types of feedback, additional sensory information would be expected to improve parameter identification (Scheidt, 2005).

The purpose of the present study was to experimentally test whether sensory information contributes to— and additional information improves—on-line parameter identification and feedback control. We tested this with a simple one degree-of-freedom task involving a resonant system. The goal was to periodically excite an underactuated rotational mass through a spring (spring-inertia system), where the mass and resonant frequency varied from trial to trial. This task was easily learned if not already familiar. However, it still required calibration of the feedback control, dependent on mass and resonant frequency, in order to successfully control the underactuated mass. We first tested whether the task involved on-line feedback and required sensory information at all, as opposed to feedforward control. We then tested whether successful interaction was improved by additional sensory information, comparing the combination of visual and haptic feedback with either alone.

II. Methods

In the following sections, we provide an analysis of the equations of motion of the spring-inertia system, which allows predictions for how the system dynamics are expected to respond to operator control. We also describe the implementation of the spring-inertia system in a virtual environment with haptic display, and discuss the design of the human subject experiments in which we manipulated the feedback conditions for this study.

A. Dynamics of the spring-inertia system

Fig. 2. With handle motion $\theta_h(t)$ a human operator can excite a lightly damped virtual inertia $I$ into oscillatory motion $\theta_1(t)$ through the virtual spring of stiffness $k$. An interaction torque $\tau(t)$ is presented through a haptic interface.

1) Analysis of System Equations of Motion: Consider the mechanical system in Figure 2 consisting of an inertia $I$ whose angular displacement $\theta_1(t)$ is driven by the angular displacement $\theta_h(t)$ of a handle through a torsional spring of stiffness $k$. The handle is driven by the user’s hand. For this second order system the damping ratio can be defined as $\zeta=b/(2\sqrt{kI})$, where $b$ is the coefficient of viscous damping. The natural frequency is defined as $\omega_n=\sqrt{k/I}$. The system equation of motion can be expressed as:

$$\ddot{\theta}_1(t) + 2\zeta\omega_n\dot{\theta}_1(t) + \omega_n^2\theta_1(t) = \omega_n^2\theta_h(t)$$

(1)

From the model expressed in Eqn. 1, we can make predictions regarding the major features of the dynamic behavior of the spring-inertia system in response to handle input motion. Note that damping present in the bearings supporting the handle is not considered in this model. Assuming that the inertia of the handle is also negligible, the torque experienced by the operator at the handle is equal in magnitude to the spring torque. The torque $\tau(t)$ is simply given by the product of $k$ and the relative angular displacement between the handle and the inertia.

$$\tau(t) = -k(\theta_1(t) - \theta_h(t))$$

(2)

Let us consider the particular control task in which a human operator excites the spring-inertia system with cyclic handle motion. As an idealization of human behavior, let us assume
that the handle is driven with sinusoidal motion of amplitude $A$ and frequency $\omega$. The resulting steady state inertia motion $\theta_h(t)$ will be a sinusoid of the same frequency $\omega$ with an amplitude gain $M(\omega)$ and a phase lag $\phi(\omega)$ relative to $\theta_n(t)$, and can be described by the expression $\theta_h(t) = A \cdot M(\omega) \sin(\omega t + \phi(\omega))$. As the driving frequency $\omega$ approaches $\omega_n$, the gain $M(\omega)$ takes on a large value and the phase $\phi(\omega)$ approaches 90 degrees. For this study, we are interested in operation of a spring and inertia with low damping, so that the natural frequency $\omega_n$ is approximately equal to the resonant frequency $\omega_r$.

We can also use our model of the spring-inertia system to develop expectations regarding the behavior of energy within the system. We can compute the instantaneous rate of work performed on the handle from the product of handle velocity $\dot{\theta}_h(t)$ and interaction torque $\tau(t)$. We then integrate this quantity to produce an expression for the work performed $W(t)$ up until the time $t$.

$$W(t) = \int_0^t k(\theta_n(T) - \theta_h(T))\dot{\theta}_h(T)dT$$

Again invoking the assumption of steady sinusoidal handle motion, the steady state work may be expressed as a function of operating frequency and time:

$$W(t) = \frac{kA^2}{2} \left[ M(\omega) \omega \sin(\phi(\omega)) \right] \cdot t$$

For sinusoidal input with a constant driving frequency, the phase and gain are fixed and the first term of Eqn. (4) exhibits a linear dependence on time. Note that maintaining a driving frequency close to resonance results in the largest value of the coefficient on $t$, which in turn requires the largest average power input from the operator. In Section II-D, these predictions concerning phase and work become the basis for developing certain performance metrics.

2) Scaling of Multiple Feedback Channels: In order to examine the effects of combining vision and haptic feedback in Experiment-2, we attempted to balance the contribution of each channel. In the manipulation of the spring-inertia system, haptic feedback is available as torque arising from the angular displacements of the spring. Thus, we controlled the scaling of haptic feedback through a selection of the stiffness $k$. For visual feedback we displayed the positions of the handle and the inertia. We make the supposition that the critical discriminatory information derived from visual feedback is not the absolute positions of the handle and mass positions, but their relative displacement. Thus, we controlled the scaling of visual information through a factor $\beta$ on the separation between the inertia and the handle $((\theta_i(t) - \theta_h(t))$, as shown in Figure 3-B. The particular values of $b$, $k$, and $\beta$ chosen for this study are given in Table II-C.2.

B. Apparatus and Implementation of Virtual Environment

We designed and constructed a manual interface with a motorized handle that rotates about a horizontal axis. Grasping a T-shaped handle with one hand, an operator can comfortably perform pronation/supination movements of the forearm. The handle is driven by a DC-motor with a 7:1 gear ratio through a chain and sprocket assembly. An optical quadrature encoder (2048 counts per revolution) attached to the axis of the motor was used to measure angular position. A desktop PC collected the measured data and controlled the motor in real-time with a sampling rate of 1 kHz. Experimental data were logged at a rate of 100 Hz.

Using this manual interface, we created a virtual representation of a spring-inertia system that could be manipulated by an operator through the rotary handle. We created a digital implementation of the dynamic behavior including haptic display as expressed in our model of the system in Eqns. (1,2). Using current and past sampled states as inputs, we employed Euler’s method for numerical integration of the system equations of motion. The computer calculated the resulting inertia position and updated the screen display. The computer also calculated the torque due to the spring deflection and sent an appropriate command signal to the motor.

Our programmable virtual environment allowed presentation of visual and/or haptic feedback according to experiment design. A computer screen displayed images of the handle and inertia positions as two beams that rotated about their centers on a common horizontal axis. The handle was shown as a smaller blue bar while the inertia was shown as a larger green bar. In addition, the inertia parameter was changed according to the experimental protocol to achieve various resonant frequencies. For both experiments I and II of this study, we fixed certain parameters as shown in Table II-C.2. A small amount of damping ($\zeta=0.0035$) between the inertia and ground was programmed for all trials. The spring constant and visual feedback scaling factor are set at $k=0.0125$ N-m/rad and $\beta=0.0075$, respectively.

C. Experimental Protocol

1) Human Subjects: In Experiment-1, eleven participants, 6 male and 5 female between the ages of 20 and 28 volunteered for the study (1 male reported being left-handed). In Experiment-2, ten participants, 7 men and 3 women between the ages of 20 and 63 volunteered for the study (1 male reported being left-handed). A chain and sprocket assembly. An optical quadrature encoder (2048 counts per revolution) attached to the axis of the motor was used to measure angular position. A desktop PC collected the measured data and controlled the motor in real-time with a sampling rate of 1 kHz. Experimental data were logged at a rate of 100 Hz.

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reported being left-handed). All participants reported having normal or corrected-to-normal vision. Each provided informed consent in accordance with University of Michigan human subject protection policies. Individuals were not paid for their participation. Participants were asked to use their dominant hand to operate the rotary handle of our apparatus.

2) Description of Motor Task: Participants were asked to excite and maintain maximum amplitude oscillations of the inertia relative to the handle motion. We did not give instructions on a strategy for best performance. Subjects performed the task while seated and were given instructions on arm and hand posture. As depicted in Figure 3, subjects grasped a motorized handle with elbow resting on a padded table top, and operated the handle using arm pronation and supination. We considered performance under various feedback conditions in separate trials each lasting 30 seconds. Before the beginning of each trial, an initial displacement of the inertia relative to the handle was set automatically. Color changes on the screen and beeps signaled the beginning and end of each trial. By rotating the handle to certain targets between trials, the subject triggered the initiation of the next trial. Subjects were allowed to begin the next trial at any time, so that the resting period prompted which feedback condition was to be given before the start of a trial, but gave no preview of the system resonant frequency. The feedback condition (See Table II-C.2) was presented in randomized order. The computer display provided from the motor, but only an image of the handle position was displayed on the screen. In Vision-Only trials, haptic feedback was provided by the motor, but images of the handle and the inertia positions were displayed on the screen. For Vision-Haptic trials, both feedback types were available.

As part of the task for Experiment-2, subjects were required to excite oscillations in a spring-inertia system without preknowledge of the system resonant frequency. For each trial, one of four possible resonant frequencies (7, 9, 11, 13 rad/s) were presented in randomized order. The computer display was only done against the inertia of the handle and against the friction/damping elements of the apparatus. Using the data collected from each trial, we numerically integrated the quantity $\tau \cdot d\theta_h$ to obtain a measure of work done. We defined a normalization factor $k(s_{\theta_h})^2$, where $(s_{\theta_h})^2$ is the within-trial variance of handle position $\theta_h$ and $k$ is the spring stiffness. A non-dimensional expression of the work done $W(t)$ is then:

$$W(t) = \frac{\int_0^t \tau(u)du \cdot \theta_h}{k(s_{\theta_h})^2} = \frac{1}{(s_{\theta_h})^2} \int_0^t [\theta_h(t) - \theta_I(t)]d\theta_h \quad (5)$$

We calculated the effective work rate $W_{av}(t)$ by examining the average work done over each trial. Use of the normalization factor allowed the comparison of success in exciting the

<table>
<thead>
<tr>
<th>EXPERIMENT-1</th>
<th>Feedback Conditions</th>
<th>No Feedback</th>
<th>Haptic Feedback</th>
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<tr>
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<tr>
<td>Trial Duration</td>
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<tr>
<td>Natural Frequencies</td>
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<th>FIXED PARAMETERS</th>
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<tr>
<td>Damping Ratio, $\zeta$</td>
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TABLE I. Experiment protocol and parameter settings.

D. Development of Performance Metrics

In this section, we present the three performance metrics that we used to examine human behavior while operating the spring-inertia system. Our first metric, the average effective work rate $W_{av}$, describes the rate of energy transferred to the virtual spring-inertia system. Secondly, using a metric we called the 'frequency specificity' $J$, we analyzed performance strictly in terms of the spectral content of handle motion. Finally, our 'phase marker variability' metric, denoted $S$, provided a measure of performance consistency that depended on the coordination between handle and inertia motion.

1) Work Analysis: As a gross measure of success in exciting oscillations of the spring-inertia system, we examined the effective work rate $W_{av}$ performed on the virtual system by the human operator. We defined the effective work measure to describe the hypothetical work that would have resulted from the recorded kinematic history of the spring-inertia system. Without externally applied haptic feedback, physical work is in fact only done against the inertia of the handle and against the friction/damping elements of the apparatus. Using the data collected from each trial, we numerically integrated the quantity $\tau \cdot d\theta_h$ to obtain a measure of work done. We defined a normalization factor $k(s_{\theta_h})^2$, where $(s_{\theta_h})^2$ is the within-trial variance of handle position $\theta_h$ and $k$ is the spring stiffness. A non-dimensional expression of the work done $W(t)$ is then:

$$W(t) = \frac{\int_0^t \tau(u)du \cdot \theta_h}{k(s_{\theta_h})^2} = \frac{1}{(s_{\theta_h})^2} \int_0^t [\theta_h(t) - \theta_I(t)]d\theta_h \quad (5)$$

We calculated the effective work rate $W_{av}(t)$ by examining the average work done over each trial. Use of the normalization factor allowed the comparison of success in exciting the
spring-inertia system for trials that exhibited differences in work performed due to the magnitude of handle motion. Note that in Eqn. (4), we considered the work done assuming sinusoidal handle input. In contrast, the effective work rate calculation in Eqn.(5) was computed based on the virtual spring torque and handle motion data collected from each trial.

A typical sample plot ($\omega_r = 7 \text{ rad/s}$) of the effective work obtained from experimental results, shown in Figure 4, exhibits behavior consistent with the assumption of sinusoidal input handle motion, described in Section II-A. A small oscillatory component with a frequency close the resonant frequency is evident in this sample plot. The effective work, however, exhibits an approximate linear increase that dominates the oscillatory component over the 30-second trial period. The average effective work rate calculated over 30 seconds as a metric for overall trial performance.

Fig. 4. The effective work as a function of time for one sample 30 second trial ($\omega_r = 7 \text{ rad/s}$) exhibits an approximately linear increase in time. The oscillatory component of the work exhibits a frequency near the resonant frequency $\omega_r$. We used the average effective work rate calculated over 30 seconds as a metric for overall trial performance.

2) Frequency Analysis: To characterize the proportion of time subjects spent driving the handle at the natural frequency for each trial, we developed a metric $\mathcal{J}$ describing the frequency specificity of the handle movement. We estimated the power spectral density $P_\omega$ using Fourier analysis of handle position data from each 30-second trial (N=3000 points, see ‘pwelch’ function, MATLAB Signal Processing Toolbox). We used an N-point Hamming window, a $2^{15}$ point FFT, and an upper frequency limit at the Nyquist frequency, or half the 100 Hz measurement sampling rate. To determine the amount of spectral energy close to resonance, we numerically integrated the power spectral density within a target frequency band of width $2\delta$ centered at the natural frequency $\omega_n$. Using the total observed spectral energy as a normalization factor, the frequency specificity $\mathcal{J}$ can be expressed as:

$$\mathcal{J} = \frac{\int_{\omega_r - \delta}^{\omega_r + \delta} P_\omega d\omega}{\int_0^{2\pi} P_\omega d\omega}$$

(6)

Normalizing the frequency specificity $\mathcal{J}$ with respect to the total spectral energy allowed us to compare differences due to spectral distribution. This normalized metric was found to be relatively insensitive to the choice of the parameter $2\delta$, which we set to 0.1 rad/s.

The sample plot in Figure 5 shows a typical distribution of power spectral density as a function of frequency. A target frequency band of width 0.1 rad/s centered at the resonant frequency of 7 rad/s is also shown. For this sample data, a relatively high of spectral density is apparent in the vicinity of the resonant frequency. However the peak spectral density appears outside the target frequency band. For trials where the spectral energy of the handle motion becomes more concentrated in the target region, $\mathcal{J}$ approaches unity. We calculated $\mathcal{J}$ for the handle position data for each 30-second trial and analyzed trends as a function of feedback condition.

3) Phase Marker Variability: We developed a metric to examine within-trial consistency in the phasing relationship between the handle and inertia position data. We defined the phase marker variability as the standard deviation (SD) of handle positions recorded at the instances $t^*$ at which sign changes occurred in the inertia velocity ($\dot{\theta}_I(t^*) = 0$). Separate phase marker variability values $S^+$ and $S^-$ were calculated for the positive and negative peak inertia excursions. The average of these expression was computed to obtain the overall phase marker variability for a single trial. The phase marker variability value was normalized by the standard deviation of the sample handle position data $\theta_h(t)$ from the entire trial, so $S$ can be expressed as:

$$S = \frac{1}{2SD(\theta_h(t))} (S^+ + S^-)$$

(7)

With the assumption of ideal sinusoidal handle motion, the expected steady state phase portrait (handle position $\theta_h$ versus inertia position $\theta_I$) is expected to exhibit an elliptical shape with the maxima of handle positions occurring at the zero handle position. By separately analyzing variability for the two separate phase marker locations and obtaining the average value, the metric $S$ provided a measure of the overall consistency of phasing behavior. Because handle motion mean amplitudes may differ across subjects and trials, the use of the normalization factor allowed a better comparison of the consistency of within-trial phasing behavior.

The sample phase plot (handle position versus inertia position) for one 30-second trial shown in Figure 6 ($\omega_r = 7 \text{ rad/s}$) exhibits typical phase marker variability. In the figure (left),

![Figure 5](https://example.com/figure5.png)

**Fig. 5.** This sample frequency distribution of handle input motion for one trial exhibits a spectral energy peak that falls outside the band centered at the 7 rad/s resonant frequency. The metric $\mathcal{J}$ revealed how much of the spectral energy for each trial was concentrated in a target frequency band 0.1 rad/s wide centered at the resonant frequency.
multiple encirclements of the origin are present with phase markers (points of maximum inertia excursion) exhibiting variability in regions at the top and bottom of the phase plot. The nominal trajectory of this sample phase plot exhibits an approximate elliptic shape. For visualization of the phase marker variability, brackets are shown centered at the mean locations of the phase markers with widths $S^+$ and $S^-$. We calculated phase marker variability using the handle and inertia position data for each 30-second trial and analyzed trends as a function of feedback condition.

E. Data Analysis

In experiment-1, we performed a paired t-test between the two feedback conditions (No Feedback/Haptic Feedback) controlling for subject (n=10) differences. In experiment-2, we first performed an analysis of variance (two-way ANOVA) considering the main effects: feedback condition (Vision-Only/Haptic-Only/Vision-Haptic), resonant frequency (7, 9, 11, 13), and subject (n=10). We then performed paired t-tests between feedback conditions (Vision-Haptic compared to Vision-Only; Vision-Haptic compared to Haptic-Only) controlling for subject (n=10) differences and averaging over trial replicates. The threshold level of significance for both ANOVA and paired t-test results for experiments 1 and 2 was set at $\alpha=0.05$. Ensemble averages were calculated as the mean over all trials in each test condition.

III. RESULTS

We analyze the results from both experiments I and II using the effective work rate, frequency specificity, and phase marker variability metrics, as described in Section II-D. We also present ensemble averaged trends of the effective work through time, spectral distributions, and phase plots for each experimental condition, shown with associated $5^{th} - 95^{th} \%$ confidence intervals across subjects. Average quantitative results for each metric are presented with associated standard deviations taken across subjects.

A. Experiment-1

In Experiment-1, we examined task performance for a fixed resonant frequency ($\omega_r=7$ rad/s) using haptic feedback alone compared to receiving no external feedback. We provided an audio tone in the beginning of the experiment to demonstrate the appropriate driving frequency.

1) Effective Work Rate: We found greater work done on the virtual spring-inertia system when haptic feedback was included. For both feedback condition in Experiment-1, plots of the average effective work trends over time and a summary of the average effective work rates are shown in Figure 7. The effective work trends indicate higher overall slope for the Haptic Feedback results, as shown in Figure 7, left. The confidence intervals for each feedback condition exhibit similar lower limits of effective work but a much higher upper limit for the condition including haptic feedback. Quantitative comparisons of the work rate averaged over 30 seconds (Fig. 7, right) showed that Haptic Feedback trials produced significantly higher values than No Feedback trials (83% higher, paired t-test, two-tailed, $p=0.001$).

2) Handle Motion Frequency Analysis: The Haptic Feedback condition resulted in handle motion with frequency content closer to the resonant frequency compared to the No Feedback condition. Ensemble plots of the power spectral density (PSD) as a function of frequency, averaged over all subjects for each feedback condition, are shown in Figure 8, left. The PSD plots of both feedback conditions indicate distributions centered close to the resonant frequency of 7 rad/s. However, the PSD results for the Haptic Feedback condition exhibited a higher peak and lower variance across subjects. Finally, our quantitative measure of frequency content showed that Haptic Feedback trials produced significantly higher $f$-scores compared to the No Feedback trials (39% higher, paired t-test, two-tailed, $p=0.003$).

3) Phase Marker Variability: We found more consistent phase behavior for trials under the Haptic Feedback condition compared to No Feedback. Ensemble phase plots (handle angular displacement versus inertia displacement) averaged over all subjects for each feedback condition are shown in
Our results also indicate that, according to the frequency specificity metric $J$, combined visual and haptic feedback channels. As representative results for Experiment-2, we present a detailed discussion for one resonant frequency, $\omega_r = 7$ rad/s.

1) Effective Work Rate: Despite changes in the resonant frequency occurring for each trial, subjects were able to achieve performance on par with that observed with a fixed frequency as in Experiment-1. The effective work trends through time (see Fig. 10) indicates slopes that are well-established in the early seconds and maintained through the 30-second trial duration.

Our effective work metric demonstrated significantly higher values with combined feedback compared to either isolated feedback condition. Ensemble mean results for each condition, as shown in Figure 10, indicate higher overall slope for the Vision-Haptic results, as well as lower within-condition variation. Quantitative comparisons showed that Vision-Haptic trials produced significantly higher effective work rate scores (83%) than Vision-Only trials (paired t-test, two-tailed, $p = 0.001$). Vision-Haptic trials also produced significantly higher values than Haptic-Only trials (23% higher, paired t-test, two-tailed, $p = 0.048$).

2) Handle Motion Frequency Analysis: Analysis of the frequency distributions of handle motion provides clear evidence that subjects successfully applied control appropriate to each spring-inertia system despite changes in the resonant frequency. Ensemble PSD plots, shown in Figure 11, left, exhibited higher density of spectral data at the resonant frequency for trials including both feedback channels. Note that each feedback conditions exhibits a ensemble averaged spectral distribution centered at the resonant frequency. In addition, confidence intervals for each distribution exclude other candidate frequencies, indicating that subjects adapted the handle motion to each resonant frequency.

Our results also indicate that, according to the frequency specificity metric $J$, combined visual and haptic feedback
produced handle data with frequency content closer to the resonant frequency compared to the use of vision alone (See Fig. 11, right). Vision-Haptic trials produced significantly higher $J$-scores than Vision-Only (39% higher, paired t-test, two-tailed, $p=0.003$). In addition, confidence intervals exhibited lowest variance in the Vision-Haptic case (See Fig. 11, left). The metric $J$ was higher for Vision-Haptic trials compared to Haptic-Only trials (+29%, paired t-test, two-tailed, $p=0.072$), though the difference did not achieve significance.

3) Phase Marker Variability: We found more consistent phase behavior for the combined feedback condition compared to either isolated feedback condition. The ensemble averaged phase plots for the Vision-Haptic case exhibited a more elliptic nominal shape and more compact confidence intervals, as shown in Figure 12. These effects indicate that using both feedback channels resulted in more ideal phase behavior. These results are in good agreement with the trends for effective input power, supporting the conclusion that providing both feedback channels caused operators to reliably achieve better performance. For all feedback conditions, the average locations of the phase markers were found to be close to zero handle position, indicating nominally appropriate phasing relationships. However, the ensemble averaged phase marker variability (marked as boxes of widths $S$) showed that the Vision-Haptic condition was more consistent. Quantitative comparisons (see Fig. 12, right) showed that Vision-Haptic trials produced significantly lower variability than Vision-Only (20% lower, paired t-test, two-tailed, $p=0.036$). Vision-Haptic trials also produced significantly lower variability than Haptic-Only (20% lower, paired t-test, two-tailed, $p = 0.036$).

The trends we found through our performance metrics were supported by analysis of variance and Student’s paired t-tests. We found significant effects ($p<0.001$, two-way ANOVA) from all metrics for both experiment factors: feedback condition (Vision-Only, Haptic-Only, Vision-Haptic) and resonant frequency ($\omega_r=7, 9, 11, 13 \text{ rad/s}$). Note, our experimental interest for this study was only in the feedback condition factor. The summary of paired t-test results for the resonant frequency $\omega_r=7 \text{ rad/s}$, shown in Table IV-C, indicates that for all three metrics used, the combined feedback condition resulted in significantly better performance compared to using vision alone. Using the effective work rate and phase marker variability metrics, the combined feedback condition resulted in significantly better performance compared to using haptic feedback alone.

We found that the performance trends between feedback conditions hold across each resonant frequency presented in our experiment. The bar plot in Figure 13 shows the effective work rate results as a function of feedback condition for all resonant frequency cases: $\omega_r=7, 9, 11, 13 \text{ rad/s}$. Considering the results for each resonant frequency separately, we found that the Vision-Haptic condition resulted in significantly better average performance than Vision-Only (paired t-test, two-tailed, $p<.0015$). However, the difference in performance between the Vision-Haptic-Only conditions reached significance only for resonant frequencies $\omega_r=7, 11, 13 \text{ rad/s}$ (paired t-test, two-tailed, $p<.048$). Similar trends were found using the frequency specificity and phase marker variability metrics. These results provide evidence that the combined feedback condition can improve performance compared to isolated feedback.

IV. DISCUSSION

A. Maintaining resonant dynamics is an on-line feedback task

Evidence from the first experiment has established that the lack of sensory feedback severely compromises the ability to drive resonant dynamics of a mechanical system, even when supplied with a preview of the resonant frequency. Each of our metrics revealed significantly degraded performance without feedback, especially in terms of the effective work trends. Evidently a strict feedforward strategy operating without the benefit of sensory feedback, as depicted in Figure 1a, can be
B. Feedback allows tuning system parameters of an existing motor program

Results showed success in exciting system oscillations despite changes in the resonant frequency, suggesting that feedback enabled on-line updates to a model-based control strategy. Each feedback condition in Experiment-2 exhibited performance comparable to the results observed when subjects were provided feedback during Experiment-1. Note in Figure 11, each spectral distribution is centered at the resonant frequency with confidence intervals that exclude other candidate frequencies. A pure feedback scheme (as in Fig. 1b), for example high gain control, cannot explain how system changes were accommodated, since delays associated with neuromotor control cause instability beyond 1 Hz. Feedback must have allowed not only movement corrections but also motor adaptation appropriate for each resonant frequency. While Schaal (1996) showed how feedback enabled human subjects to identify stable control strategies in a ball bouncing task, the current experiment reveals on-line adaptation to specific changes in the dynamics of an extrinsic object.

C. Higher quality sensory information aids on-line control

When sensory feedback was available in Experiment-1, it came only in the form of haptic feedback. Therefore, haptics must have provided the necessary information for on-line control. Force interactions in the control of a spring-inertia system reflect the continuous variation of spring deflection—information which is certainly useful for on-line control of phasing. While including discrete haptic pulses has been shown to aid performance in the control of a simulated bouncing ball task (Sternad 2000), our results extend those findings by demonstrating the viability of continuous haptic feedback as an information channel for the control of an extrinsic object.

The results of Experiment-2 show that greater sensory information facilitates more accurate tuning to a resonant mechanical system. The advantages of combined feedback were most evident in the time-domain metrics—those that reflect the use of feedback on-line. Higher effective work rate and lower phase marker variability (See Figures 10, 12) resulted with combined feedback, indicating superior coordination between arm and inertia states. The lack of significant differences in frequency specificity suggests an ability to maintain appropriate rhythmic arm movement independent of feedback condition. Subjects evidently used available information to establish a nominal rhythmic pattern, but found combined feedback most useful for refining real-time control. Just as the presence of a single channel facilitated on-line control in Experiment-1, the superior performance from combined visual and haptic feedback suggests more effective tuning occurred.

But even when provided alone, vision or haptic feedback allowed considerable success in control for systems with initially unknown resonant frequencies. In contrast to Experiment-1, where performance was compared with and without feedback, differences between feedback conditions in Experiment-2 were less dramatic, suggesting each channel provided the information necessary to first identify the resonant frequency and then maintain phasing. As described in the Methods section, handle motion alone dictates the evolution of extrinsic states, so that force interactions are not in principal required for control. However as shown in Experiment-1, some form of

![Effective Work Rate Trends](image)

For all resonant frequencies tested, quantitative comparisons of the trial average performance showed that the combined feedback condition resulted in the higher average effective work rate (right, with 1 s.d. shown).
feedback was necessary simply to maintain phasing. While the inclusion of both haptic and visual feedback most realistically reflects the behavior of physical systems, either channel alone can provide the necessary information about the states of the spring-inertia system.

In summary, the two experiments in this study have shown that sensory feedback is required for the control of mechanical resonance both in terms of maintaining phasing during online control and in tuning to a system with unknown resonant frequency. With our motor task involving the excitation of the resonant dynamics of a spring-inertia system, we have begun to investigate two important features of the human motor control system that employ sensory feedback: on-line movement corrections and tuning to object properties of a system with familiar dynamic behavior (resonance). We have also established that for the motor task in this study, haptic feedback can serve not only for the learning of appropriate motor command patterns, but also in the capacity of a sensory channel for online movement corrections. Like visual feedback, we have found that haptic information allows the perception of extrinsic states of an underactuated system. Furthermore, we have shown the benefits of combined vision and haptic feedback, providing evidence that the human motor system employs a control scheme that integrates sensory feedback with an internal representation of an underactuated system for improved performance.

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REFERENCES


