

Passive and Active Discrimination of Natural Frequency of Virtual Dynamic Systems

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Abstract—It has been shown that humans use combined feedforward and feedback control strategies when manipulating external dynamic systems and when exciting virtual dynamic systems at resonance and that they can tune their control parameters in response to changing natural frequencies. We present a study to determine the discrimination thresholds for the natural frequency of such resonant dynamic systems. Weber fractions (WF, %) are reported for the discrimination of 1, 2, 4, and 8 Hz natural frequencies. Participants were instructed either to passively perceive or actively excite the virtual system via a one degree-of-freedom haptic interface with visual and/or haptic feedback. The average WF for natural frequency ranged from 4% to 8.5% for 1, 2, and 4 Hz reference natural frequencies, while the WF was approximately 20% for systems with a reference natural frequency of 8 Hz. Results indicate that sensory feedback modality has a significant effect on WF during passive perception, but no significant effect in the active perception case. The data also suggest that discrimination sensitivity is not significantly affected by excitation mode. Finally, results for systems with equivalent natural frequencies but different spring stiffness indicate that participants do not discriminate natural frequency based on the maximum force magnitude perceived.

Index Terms—Active and passive touch, Weber fractions, natural frequency discrimination, virtual resonance task, rhythmic movements.

1 INTRODUCTION

HUMANS frequently perform motor tasks that require interactions with external dynamic systems, such as driving a car or wielding a tool. Some systems may not be directly coupled to the user, requiring manipulation of unactuated degrees of freedom [1]. Other systems may have higher order control mappings between inputs and outputs, such as piloting an aircraft, which require training in order for the human to learn proper control [2]. For rhythmic tasks such as pumping a swing or bouncing a ball, the perception of the dynamic behavior of the external system directly affects the control input planned and executed by the user [3]. However, psychophysical analysis of actively controlled dynamic systems, which may shed light on the mechanisms used by humans to execute motor tasks, has received little attention. A broader understanding of human motor control could directly benefit researchers who develop training protocols or simulations to teach new motor skills.

In an effort to improve training efficacy for motor tasks in virtual environments, researchers have attempted to integrate haptic guidance through the use of shared control strategies, which dynamically intervene with the user to modify the coupled task and shared controller dynamics

during training [4]. There exists wide variability in the results of user studies on the effectiveness of shared control haptic guidance for improving training efficacy. For example, Patton and Mussa-Ivaldi [5] trained new reaching movements by generating custom force fields, which were designed to drive subjects to adapt a predefined trajectory. However, the observed after-effects washed out after a short period of time. Error amplification strategies have been used successfully to speed up human motor learning of a dynamic task [6], [7], though error reduction in a dynamic target-hitting task showed negative training efficacy [8].

In order to better design shared control haptic guidance schemes that will produce positive outcomes for training of manipulation and motor tasks, it is desirable to gain a deeper understanding of human motor skill execution and acquisition. We hypothesize that the ability to learn new motor skills depends on the ability to form a control model and to tune control parameters. To tune control parameters, one must perceive the dynamic behavior of the excited system. We investigate manipulation of second-order dynamic systems, which can be characterized by their natural frequency. Shared control algorithms have the potential to accelerate the parameter tuning process by focusing user attention and skill refinement on key dynamic properties of the controlled systems, thereby improving learning times and training efficacy.

It has been shown that humans can adapt their feedforward control commands over time [5], [9]. This adaptation can be viewed as successful training of a new skill. Control parameter adaptation during object manipulation was observed by Huang et al. [10] in a recent study of online control during object manipulation. They investigated a

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simple rhythmic object manipulation task in a virtual environment and determined that subjects could identify and excite distinct virtual system natural frequencies with visual only, haptic only, or combined visual and haptic feedback. They observed that participants appeared to tune control parameters of a general feedback strategy.

We are interested in the mechanisms by which humans adapt their control parameters when manipulating external dynamic systems, with the intention of using such information to better design shared control algorithms. As a first step, we explore the ability of humans to resonate virtual mechanical systems with distinct natural frequencies, which was observed by Huang et al. [10]. Just as information from sensors in an adaptive control system can be used to tune a feedforward model or adjust a feedback controller, the human's ability to sense dynamic behavior of a controlled system is a key capability required to adapt their own control parameters. In this study, we investigate the human's sensitivity to changing resonant frequency of a manually excited virtual dynamic system.

A human's sensitivity to dynamical systems has been explored in terms of all three mechanical parameters forming a second-order system. These parameters are inertia, viscous damping, and spring stiffness, all of which are derived from force and movement derivatives. The discrimination thresholds of inertial forces were determined by Beauregard et al. [11] by squeezing two plates between the finger and the thumb. The average Weber fraction (WF in %) was 21%, which was significantly greater than the fractions reported for weight and force discrimination [12], [13]. Brodie and Ross [12] reported weight Weber fractions (WF, in %) in the range of 9%-13% by lifting (active) or placing weights on the palm (passive) of their participants' hands. The variability in the results of the two studies could be attributed to the absence of specific receptors for the perception of inertia, whereas weight can be discriminated by force sensors embedded in the skin, joints, and muscles [14]. Similar to the inertia WF, large thresholds were obtained for stiffness and viscosity discrimination. The reported WFs are in the range of 7% and 23% for stiffness (or compliance) discrimination [15], [16], [17], while the viscosity WFs are in the range of 14%-34% [11], [18], [19]. The variability in the fractions is mainly due to the experimental procedures and the terminal forces and work cues during a trial (see [15] and [18]). The results in these studies were interpreted as the loss of perceptual resolution when the discrimination task requires a combination of force and displacement or its derivatives.

The natural frequency of a dynamic system is a function of inertia and elastic stiffness of the system and can be thought of as one signature of the system's inherent behavior. Although many studies have determined passive frequency discrimination thresholds, we are not aware of any data on active frequency thresholds or natural frequency thresholds. The vibrotactile and kinesthetic frequency WFs (passive case) varied from 2% to 72%. Variability in the size of WFs was largely due to different experimental conditions, stimulus parameters (frequency and amplitude), and the presence of another stimulus (the masker) along with the target stimulus (see a review in [20]).

In the present study, the first objective is to determine the influence of excitation mode on a human's ability to discriminate the natural frequency of virtual dynamic systems. We ask participants to actively excite the system while coupled with the handle of a single degree-of-freedom haptic device. The device displays dynamical forces on the handle grasped by the participants. In order to compare the discrimination performance with the case when interaction forces of the system are presented on the passive hand, natural frequency WFs are also measured by exciting the dynamic system with an external source, while participants passively hold the handle of the haptic device.

A second objective of the present study is to investigate the influence of different sensory feedback (vision, haptics, or combined) on discrimination ability. In the manual control task, it is important to understand the potential assistance that can be provided by haptic-only or visual-only feedback, or if combining haptic with visual feedback is better than incorporating them individually. Previous studies have reported the effectiveness of multisensory feedback in different experimental tasks. For example, in a dynamical task, Sternad et al. [3] investigated rhythmic bouncing of a ball with a racket and concluded that the inclusion of haptic feedback enhanced stability performance compared to when visual information was presented alone. Morris et al. [21] performed a force skill learning task by presenting temporal force patterns on a passively moving human hand along spatial trajectories. The task was to recall a force pattern in a test trial that was presented in a training trial with haptic-, visual-, or combined feedback. Their results showed that accurate recall was marginally higher with visual-training than with haptic-training, but combined visual and haptic training resulted in significantly higher accuracy than visual- and haptic-training alone. In a manual excitation task, Huang et al. [10] reported that haptic feedback augmented with vision significantly improved the control of their dynamic system compared to either modality alone.

In the present study, WFs are determined for 1, 2, 4, and 8 Hz reference natural frequencies in three series of experiments. In order to investigate if haptic feedback assists in the discrimination task, visual-only (V), haptic-only (H), and combined visual and haptic (V + H) feedback are presented in both the passive and active excitation modes. The remainder of the paper is organized as follows: Section 2 describes the experimental methods, and Section 3 presents the results of the experiment. We discuss the results in Section 4, followed by conclusions in Section 5.

2 METHODS

2.1 Apparatus

The experimental apparatus consists of a one degree-of-freedom custom-built impedance-type haptic device that displays forces on a palm grip handle, as shown in Fig. 1. The forces generated at the handle are proportional to the current applied to the DC motor (Faulhaber, 3557K024C) that serves as an actuator of the device. The output voltage of the DAC (digital-to-analog converter) is passed through a voltage-to-current amplifier (Advanced Motion Controls, model 12A8M) to drive the motor. The amplifier gain is

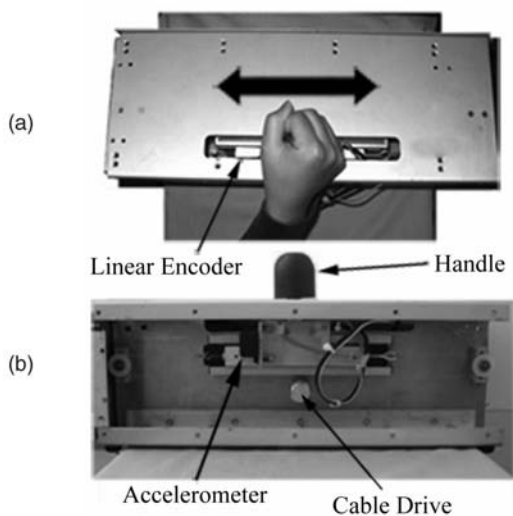


Fig. 1. One degree-of-freedom haptic interface, (a) top view and (b) front view.

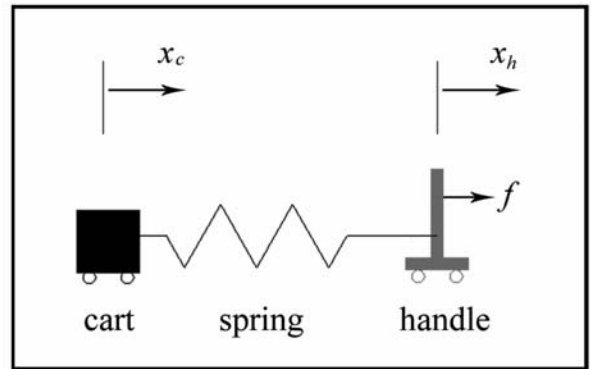
selected such that 1 Volt at the DAC corresponds to 8 mNm of torque applied by the motor. The motor is mounted on a cable drive with a radius of 10 mm. The handle assembly is driven by a cable-and-pulley drive system and translates on a ball-slider (Del-Tron Precision Inc., model S2-6) with low friction. High stiffness fishing wire (American Fishing Wire, grade 26 lbs nylon coated 7×7 stainless steel, 16 N/mm stiffness) is used to connect the moving handle assembly with the cable drive, as shown in Fig. 1. The motor has small friction torque, and the pulleys are mounted on high performance bearings to reduce the effects of friction. The bandwidth of the device is determined to be about 30 Hz.

A position encoder (Renishaw RGH24X) and an accelerometer (Crossbow Technology Inc., model CXL02LF1Z) are mounted on the handle assembly to measure the handle's instantaneous states, which are used to render interaction forces characterizing the virtual dynamical system. The haptic device synthesizes a virtual resonance task by rendering a linear mass-spring system, as shown in Fig. 2b. The sensed motion of the handle is used to excite a virtual spring that is connected to a virtual cart of specified mass. Open loop impedance control with model-based inertia compensation is implemented to render the virtual task dynamics. Acceleration feedback from the handle is used to compensate for the apparent inertia of the device, estimated to be 0.42 kg. No friction compensation is employed since the (viscous and Coulomb) friction of the device is found to be minimal (in the worst case, approximately 11 percent of the rendered forces, see the Appendix).

When the handle is excited either by the computer system (passive case) or by a human participant (active case), the resulting motion of the virtual cart is determined solely by the dynamics of the virtual system and is graphically displayed to the user along with an image of the handle position (see Fig. 2a). The haptic and graphical simulations are processed by two different CPUs connected through a serial channel. The haptics loop runs at 1 kHz, and the graphical loop updates at a rate of 33 frames per second. The refresh rate of the computer monitor displaying the graphical image is set to 72 Hz.



(a)



(b)

Fig. 2. Discrimination experiment setup, (a) showing the 1-DOF haptic device held by the participant and dual screen display. (b) shows the graphical display of the virtual environment consisting of a cart and handle system connected by a spring.

2.2 Participants

Eight males and two females (S1-S10, Rice University students at the time of testing, 19-31 years old, average age 24) took part in the study. S1 was tested in all experimental conditions, while others were tested in fewer conditions, depending on their availability. All participants were right handed by self-report and had no known hand or arm impairments. All participants except one had prior exposure to haptic or force feedback devices.

2.3 Stimuli

This study employed a stimulus that was derived from the spring and mass parameters of the virtual system shown in Fig. 2b. The dynamical forces are derived from solving the following differential equation using the backward Euler method of numerical integration:

$$\ddot{x}_c + 2\xi\omega_n\dot{x}_c + \omega_n^2x_c = 2\xi\omega_n\dot{x}_h + \omega_n^2x_h, \quad (1)$$

where \ddot{x}_c , \dot{x}_c , and x_c are respectively the acceleration, velocity, and position of the cart, while \dot{x}_h and x_h are velocity and position of the handle. ξ is the damping factor and is very small (less than 0.02), and ω_n is the undamped natural frequency of the second-order dynamics, i.e., $\omega_n = \sqrt{k/m}$.

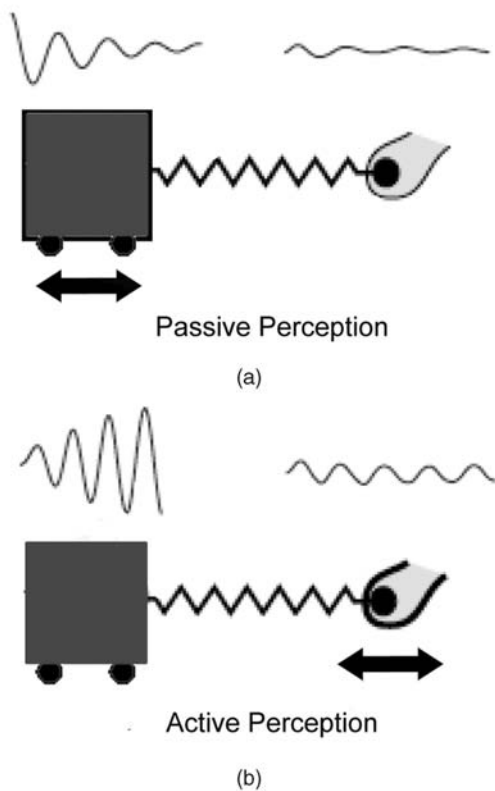


Fig. 3. Typical trajectories of (left) handle position/human input and (right) virtual cart trajectories versus time for (a) passive perception and (b) active perception.

In each trial of the experiment, participants were presented either with the system of a reference natural frequency (ω_0) or with the system of a test natural frequency ($\omega_0 + \Delta\omega$) with equal a priori probability; where $\Delta\omega$ was the increment in natural frequency. In order to focus the participant's attention on the natural frequency and eliminate the effects of force and position magnitudes on the discrimination experiment, equivalent systems with two different spring stiffnesses were associated with each natural frequency. Thus, the reference natural frequency was derived from either parameter set (m_{11}, k_1) or (m_{12}, k_2) , and the test natural frequency was derived from either (m_{21}, k_1) or (m_{22}, k_2) , with equal probabilities of encounter. The spring stiffness values used for each natural frequency were $k_1 = 25$ N/m and $k_2 = 35$ N/m. Rendered forces and handle and cart displacement profiles with all four mass and stiffness combinations for the 1 Hz reference natural frequency in both the active and passive excitation modes are presented, in the Appendix. In the passive perception cases, the duration of a trial was randomly selected from ten equally spaced levels between 4 and 6 seconds in order to eliminate cues, such as differentiating natural frequency by counting the number of oscillations in a trial. In the active perception cases, the duration of each trial was fixed at 5 seconds.

2.4 Procedure

Participants sat comfortably in front of two computer screens, and the one degree-of-freedom device resided on a table to the right of their torso. They placed their elbow on the table with the haptic device and held the handle of the

TABLE 1
Summary of Experimental Conditions

Experimental Condition	Exciting Case	Sensory Feedback	Ref. Natural Frequency (Hz)
1	Passive	Visual-only (V)	1 and 2
2	Passive	Haptic-only (H)	1, 2, 4 and 8
3	Passive	Visual+Haptic (V+H)	1, 2, 4 and 8
4	Active	Visual-only (V)	1 and 2
5	Active	Haptic-only (H)	1 and 2
6	Active	Visual+Haptic (V+H)	1 and 2

device, as shown in Fig. 2a. The screen on the left displayed the main experiment graphical user interface (GUI) for participants to select their responses. The right-hand screen provided real-time animation of the virtual system. The one degree-of-freedom force feedback device conveyed interaction forces due to the dynamics of the virtual handle-cart system, shown in Fig. 2b, to the participant's hand.

The experiments were conducted for two excitation cases. The first case is when no active excitation is applied by the participant, and the computer system excites the virtual mass-spring system with an initial displacement between the virtual cart and the handle. No other forces were added by the computer system during a trial, and the cart motion gradually decayed due to the hand contact and virtual damping of the second-order system. This case is referred to as the "passive perception mode," see Fig. 3a, and the participant passively perceives the dynamic response of the oscillatory virtual system. The second case is when the participant constantly excites the virtual system with approximate sinusoidal motion to match with the natural frequency of the system. This case is referred to as the "active perception mode," Fig. 3b. Unlike most psychophysical procedures where stimulus parameters are controlled during the experiment and presented on passive humans, in the active perception mode the amplitude of the displacements (both cart and handle) and the forces depend on human voluntary motion. Typical trajectories of the virtual cart and the handle in both excitation cases are illustrated in the Appendix.

Three types of sensory feedback were provided in the passive and active perception modes as summarized in Table 1. For the visual-only (V) conditions in the passive perception mode, participants received motion cues by monitoring the movement of the virtual handle-cart system displayed on the computer screen to their right. For the visual-only conditions in the active perception mode, participants excited the handle of the haptic device that displayed forces only to compensate for the apparent inertia of the haptic device. For the haptic-only (H) conditions, the computer monitor with graphical representation was turned off. The participants were instructed to focus on the interaction forces by either holding or exciting the physical handle of the one-degree-of-freedom device. For the combined visual and haptic (V + H) conditions, both visual and haptic cues were presented to participants simultaneously. The WFs are estimated in all six experimental

conditions at 1 Hz and 2 Hz reference natural frequencies and in the haptic and visual + haptic feedback conditions at 4 Hz and 8 Hz reference natural frequencies in the passive mode. A summary of the discrimination experiment is explained in Table 1.

The discrimination thresholds were estimated using the one-interval two-alternative forced-choice (1I-2AFC) procedure of signal detection theory [22]. In each trial, the participant was presented with a system that had either the reference natural frequency (ω_0) or the test natural frequency ($\omega_0 + \Delta\omega$). The participant's task was to select either a button marked "lower frequency" (to select the reference frequency) or a button marked "higher frequency" (to select the test natural frequency) based on their perception of the virtual dynamic system behavior. Correct answer feedback was provided after the completion of every trial. Each experimental condition was tested for three increment frequencies, namely, 5 percent, 10 percent, and 15 percent of the reference natural frequency. The order of presentation of each increment frequency run was randomized and tested in a single session with sufficient rest between each run. The reference and test natural frequency remained the same within one experimental run. Each run had 80 trials and lasted about 15 to 25 minutes. Out of 80 trials, the first 16 were training, and the next 64 were test trials. Thus, for one reference natural frequency and experimental condition, each participant was tested for 240 trials in one session (overall, 19,200 trials were collected in the entire experiment).

The entire set of experimental conditions and reference natural frequencies were tested in three series of experiments by ten participants. A summary of experiment series and the participants tested is presented in the first four columns in Table 2. In the first series, six participants took part in determining the thresholds at 1 Hz and 2 Hz reference natural frequencies, with three feedback conditions in the passive mode and H and V + H conditions in the active mode (i.e., experimental conditions 1, 2, 3, 5, and 6). Four participants (S1, S2, S3, and S4) were tested for both reference natural frequencies, and the two remaining participants (S5 and S6) were tested at only one reference frequency each. The order of the reference frequency was randomized for all participants, but the order of sensory feedback and excitation cases in the five conditions was the same, as that shown in Table 1. This helped the participants to gain familiarity with the task due to the difficulty in discriminating frequencies with limited sensory feedback. At the end of this series, S1, S2, and S6 were retested in some cases of condition 1 to determine the potential effects of training. No such effects were observed, and the original data were stored for analysis. After the completion of five conditions at 1 Hz and 2 Hz natural frequencies, five participants (S1, S6, S8, S9, and S10) were tested in the visual-only condition at 1 Hz and 2 Hz natural frequencies. Again, the order of the reference frequency was randomized among participants. Finally, four males and one female participant (S1, S6, S7, S8, and S9) were tested at 4 Hz and 8 Hz reference natural frequencies in the haptic and visual + haptic combined feedback passive conditions (see Table 1). The order of the reference frequency and sensory feedback were randomized. At the end of each experiment series, performance scores were determined, and some participants were

asked to repeat runs that showed unusual performance indices. Unusual performance was defined as a performance equal to or less than the chance level. Overall, 8 out of 240 runs (3.3 percent of the total number of trials) were repeated in the entire experiment, and the new data was used in analysis.

The participants received instruction before each day's testing and were given a few training trials to familiarize themselves with the experimental task. In all conditions, participants were instructed to avoid looking at the haptic device or their hand motion in order to judge the natural frequency. Participants were explicitly told to focus on the computer screens and not to look at their hands or the apparatus during a trial. To increase the likelihood that participants would follow the given instructions, they were required to interact with a GUI on a computer screen in front of them that required significant visual attention. During the experiment, pink noise was presented through headphones to eliminate possible auditory cues from the environment and hardware. A cardboard and cloth screen was placed in front of and around the participant to isolate the testing setting from the outside environment. All participants signed consent forms before the experiment and all experiments were completed with the preapproved IRB policy of Rice University. After testing, participants completed a questionnaire about their familiarity and interests in video games, multitasking, and motor tasks.

2.5 Data Analysis

A 2×2 stimulus-response matrix resulting from the last 64 test trials of a run was analyzed to estimate the thresholds for four natural frequencies and six experimental conditions. Using the assumption that the underlying density functions associated with the two natural frequencies being discriminated in each run were normal (Gaussian) and of equal variance, the sensitivity index (d') and response bias (β) were determined as

$$d' = Z(H) - Z(F) \quad (2)$$

and

$$\beta = -\frac{Z(H) + Z(F)}{2}, \quad (3)$$

where H is the hit rate of the test stimulus, and F is the false alarm rate. $Z(\cdot)$ is the inverse function of the normal Gaussian distribution and is determined by transforming the cumulative probability under the normalized Gaussian density curve to standard deviation units [22]. An unbiased response is indicated by $\beta = 0$. The performance threshold for natural frequency Weber fraction is set as $d' = 1$.

Generally, the value of d' is roughly proportional to the increment at each natural frequency and experimental condition. In Tan et al. [15], the threshold was estimated by first determining the best fit slope $\delta' = d' / (\Delta\omega / \omega)$ from several increment cases, and the inverse of the slope was an estimate of WF (reported as JND in percent). In the present study, each increment case is used to obtain a slope $\delta = d' / (\Delta\omega / \omega)$. The WF is determined when $d' = 1$. Thus, given the slope δ and $d' = 1$, the inverse of the slope results in an estimate of natural frequency WF, $(\Delta\omega)_0 / \omega$. The mean WF for each condition is the average WF obtained at three increment cases pooled across participants at that condition.

TABLE 2
Summary and Result of Discrimination Threshold Experiment

Natural Frequency (Hz)	Experimental Condition	Experiment Series	Participants	Natural Frequency Weber Fractions (%)		Response Bias	
				Average	Std. Error	Average	Std. Error
1	1	I	S1,S2,S3,S4,S5	5.12	0.30	-0.03	0.07
1	2	I	S1,S2,S3,S4,S5	6.96	1.06	0.04	0.05
1	3	I	S1,S2,S3,S4,S5	3.99	0.33	0.07	0.09
1	4	II	S1,S6,S8,S9,S10	8.52	1.70	0.06	0.08
1	5	I	S1,S2,S3,S4,S5	6.50	0.72	0.11	0.09
1	6	I	S1,S2,S3,S4,S5	5.62	0.47	-0.02	0.07
2	1	I	S1,S2,S3,S4,S6	5.07	0.64	0.07	0.06
2	2	I	S1,S2,S3,S4,S6	6.82	0.92	-0.04	0.07
2	3	I	S1,S2,S3,S4,S6	4.52	0.33	-0.02	0.06
2	4	II	S1,S6,S8,S9,S10	6.90	1.71	-0.01	0.07
2	5	I	S1,S2,S3,S4,S6	5.65	0.51	0.11	0.08
2	6	I	S1,S2,S3,S4,S6	5.07	0.79	0.02	0.07
4	2	III	S1,S6,S7,S8,S9	7.71	0.82	0.03	0.05
4	3	III	S1,S6,S7,S8,S9	7.15	1.03	-0.11	0.07
8	2	III	S1,S6,S7,S8,S9	10.44	2.25	0.10	0.05
8	3	III	S1,S6,S7,S8,S9	19.75	5.92	0.15	0.05

Analysis of variance (ANOVA) is utilized to determine significant differences of natural frequency WF between experimental conditions and reference frequencies. The d' obtained in one increment case resulted from 64 trials and each estimate of the WF is considered as an independent observation in the ANOVA, yielding 180 (two frequencies, six experimental conditions, three increment cases, and five participants per frequency) estimates of WF at 1 Hz and 2 Hz reference natural frequencies and 60 (two frequencies, two experimental conditions, three increment cases, and five participants per frequency) estimates of WF at 4 Hz and 8 Hz natural frequencies. In order to further explore the influence of different sensory feedback on the natural frequency WF, another statistical analysis method, the difference of least square means, is used. This analysis method takes into account all the WFs for different conditions by using an adjusted mean for each condition that isolates the effect of each individual condition and then gives out specific comparisons between each pair of conditions [23]. In this way, we can compare all six experimental conditions at different reference natural frequencies, such as visual-only at 1 Hz versus haptic-only at 1Hz, while typical posthoc tests can only give comparisons between visual-only and haptic-only conditions combined for both 1 Hz and 2 Hz.

3 RESULTS

For each experimental run, sensitivity index (d') and response bias (β) were calculated using Equations (2) and (3). A large variation in the natural frequency WF was observed among participants, reference natural frequency, excitation modes, and feedback condition. In order to highlight the effects of frequency, excitation modes, and feedback conditions, the data is pooled together among participants. The summary of experimental results (WF in %

and the response bias) and the participants tested in each experimental condition and series are presented in Table 2.

Note that no significant bias was observed in any of the experimental conditions and $|\beta| < 0.2$. Overall, the average bias was $\beta = 0.03$ (std. dev. 0.27) for all experimental conditions and reference natural frequencies. The 95 percent confidence bound of a true mean bias using the Student's t-test ($df = 239$) was $[-0.001, 0.06]$. Notice that the zero bias is within the confidence bound. Near zero response bias indicates that the participants were on the average not biased toward any particular response and were consistent in following experiment instructions. In each run, stiffness values were presented with equal probability of occurrences at each natural frequency (reference and test). With $k_1 = 25$ N/m, on the average the participants were slightly biased toward clicking "higher frequency" more often than "lower frequency" (average $\beta_1 = 0.10$, standard deviation 0.47, and 95 percent confidence bound $[0.04, 0.16]$). With $k_2 = 35$ N/m, no significant bias was observed (average $\beta_2 = -0.02$, standard deviation 0.39, and 95 percent confidence bound $[-0.07, 0.02]$), i.e., participants were equally likely to respond "lower frequency" and "higher frequency." The relatively high standard deviation indicates variation in the participants' bias toward one stiffness value and response choice. Satisfactory biases are the evidence that participants were not influenced by the force and/or stiffness cues (as indicated in [15] for compliance discrimination), and natural frequency was discriminated independent of force magnitude cues.

In the first experiment series, a repeated measures ANOVA (reference natural frequency as a between-subjects factor, experimental condition as a within-subjects factor) showed that reference natural frequency did not have a significant effect on the WFs [$F(1, 28) = 0.21, p = 0.654$], and experimental condition effects were significant [$F(4, 25) = 12.38, p < 0.001$]. The interaction term was not

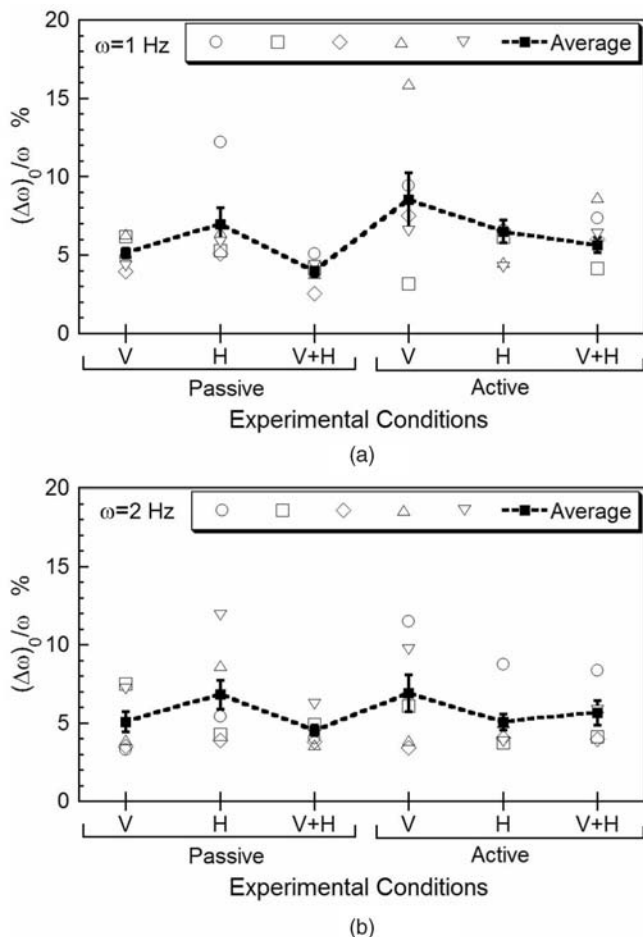


Fig. 4. Weber fractions (in %) for five participants and their average at (a) 1 Hz and (b) 2 Hz reference natural frequencies in the six experimental conditions. Each open symbol is the average of three WF values. The order of participants in the legend is the same as the order shown in Table 2. Error bars represent the standard error of the mean

significant [$F(4, 25) = 0.91, p = 0.47$], indicating similar trends in experimental conditions at the two reference natural frequencies.

The average WFs (in %) in the six experimental conditions at 1 Hz and 2 Hz reference natural frequencies (experiment series I combined with experiment series II) are shown in Fig. 4. Error bars show the standard error of the mean pooled across participants. Also shown in the figure are the average WFs of three increment cases for each participant at 1 Hz (Fig. 4a) and 2 Hz (Fig. 4b) reference natural frequencies. The order of the participants in the figure legend is the same as that reported in Table 2, column 4. The average WF varied from 4% to 8.5% at 1 Hz and from 4.5% to 6.9% at 2 Hz reference natural frequencies. At both reference natural frequencies, the smallest thresholds were obtained with visual + haptic combined feedback in the two excitation modes, while the largest thresholds occurred with haptic-only feedback in the passive perception mode and visual-only feedback in the active perception mode. A summary of significant differences between experiment conditions measured by the difference of least square means method are listed in Table 3. An asterisk indicates statistical significance. Notice that the difference between H and V + H conditions in the passive perception cases is significant ($p < 0.05$) or marginally significant ($p = 0.05$) at 1 Hz and 2 Hz, indicating

better discrimination ability with combined visual and haptic feedback versus haptic only feedback. No such significance was observed between other feedback conditions at both reference frequencies. In all six experimental conditions, the data failed to show significant differences in WF between 1 Hz and 2 Hz natural frequencies and between active and passive perception modes, except for the comparisons involving 1 Hz reference frequency in the active mode with visual only feedback. This could be due to large variability in the WFs among participants (see Fig. 4a).

Fig. 5 shows the natural frequency WFs obtained at 4 Hz and 8 Hz natural frequencies (experiment series III) in conditions 2 and 3 and compares them with corresponding WFs at 1 Hz and 2 Hz natural frequencies (experiment series I). Error bars represent the standard error of the means. Also shown in the figure are the mean WFs for each participant at 4 Hz and 8 Hz frequencies. The data points are slightly shifted along the abscissa to distinguish WFs between H and V + H conditions.

A repeated measures ANOVA analysis (reference natural frequency as a between-subjects factor, experimental condition as a within-subjects factor) showed that natural frequency had a significant effect on WF [$F(3, 56) = 6.23, p < 0.01$], while the data failed to show any significant difference in WF due to experimental condition [$F(1, 56) = 0.34, p = 0.56$]. The significant interaction term [$F(3, 56) = 3.72, p = 0.02$] indicated mixed trends of the natural frequency and feedback conditions. A posthoc multirange Scheffe test separated the natural frequencies into two sets. The mean WF of one set (1 Hz, 2 Hz, and 4 Hz) was significantly smaller than that of the other set (8 Hz), whereas no significant differences were observed between the frequencies of each set. The repeated measure ANOVA tests for individual frequencies (feedback as a within-subjects factor and participant as a between-subjects factor) showed that the two experimental conditions (H and V + H) at 1 Hz and 2 Hz natural frequencies are significantly different ($p < 0.05$), while the data failed to show significance of feedback conditions at 4 Hz and 8 Hz ($p > 0.05$). The between-subject effects were significant ($p < 0.01$) at all frequencies indicating variability in the WF among participants, but nonsignificant interaction terms ($p > 0.05$) suggested nonsignificant trends with feedback by all participants. With haptic-only feedback, a one-way ANOVA (natural frequency as a factor) showed that the WFs were not significantly different at the four frequencies [$F(3, 56) = 1.48, p = 0.24$] and with V + H feedback, the WFs at 8 Hz were significantly larger than the WFs at other reference natural frequencies ($p < 0.01$).

4 DISCUSSION

In this study, we determined discrimination thresholds for the natural frequencies of virtual dynamic systems. Our goals were to determine the effect of excitation strategy (passive or active), feedback modality (visual only, haptic only, or visual + haptic), and reference natural frequency (1, 2, 4, or 8 Hz) on a human's ability to discriminate resonant frequencies in virtual dynamic systems rendered with a 1-DOF haptic device and an accompanying visual display.

TABLE 3
Summary of Significance Measured by Differences of Least Square Means

Natural Frequency	Sensory Feed-back	Excitation Case	p-value
1	V vs. H	Passive	0.13
1	V+H vs. H	Passive	0.01*
1	V+H vs. V	Passive	0.35
1	V vs. H	Active	0.10
1	V+H vs. H	Active	0.47
1	V+H vs. V	Active	0.02*
2	V vs. H	Passive	0.15
2	V+H vs. H	Passive	0.05*
2	V+H vs. V	Passive	0.65
2	V vs. H	Active	0.30
2	V+H vs. H	Active	0.64
2	V+H vs. V	Active	0.13
1 vs. 2	V	Passive	0.97
1 vs. 2	H	Passive	0.91
1 vs. 2	V+H	Passive	0.66
1 vs. 2	V	Active	0.18
1 vs. 2	H	Active	0.48
1 vs. 2	V+H	Active	0.65
1	V	passive vs. active	<0.01*
1	H	passive vs. active	0.70
1	V+H	passive vs. active	0.18
2	V	passive vs. active	0.13
2	H	passive vs. active	0.33
2	V+H	passive vs. active	0.65

* Statistically significant, $p < 0.05$ or marginally significant, $p = 0.05$.

We hypothesize that skill acquisition for manual control tasks requires the ability to tune control parameters to compensate for errors, disturbances, or time-varying model parameters. In order for a human to adapt their control

strategy, they must be able to perceive variations in dynamic behavior of the controlled system. This study explores the ability of humans to resonate virtual mechanical systems with distinct natural frequencies, observed by Huang et al. [10]. Our long-term objective is to use these results to design shared controllers or virtual guidance schemes that augment the dynamics of the motor task in such a way as to increase the rate of control parameter adaptation, thereby speeding the process of skill acquisition and decreasing the time required to attain expertise. It is important to understand the thresholds of human perception of system dynamics so that virtual guidance can be used effectively for training of dynamic tasks. For example, combined visual and haptic information may produce better performance than visual feedback alone [3], [10], [21]. Similarly, it may be useful to convey desired manipulation schemes while the user remains passive, rather than requiring active manipulation by the user.

First, the method of manipulation of the virtual system was varied to determine if active excitation produced different results from passive excitation. Previous studies have determined the frequency and period discrimination thresholds (or WF) for low-frequency sinusoidal waveforms on passive fingerpads [20], [24]. However, a human's ability to discriminate the natural frequency of a manually excited dynamic system has not been reported in the literature. The

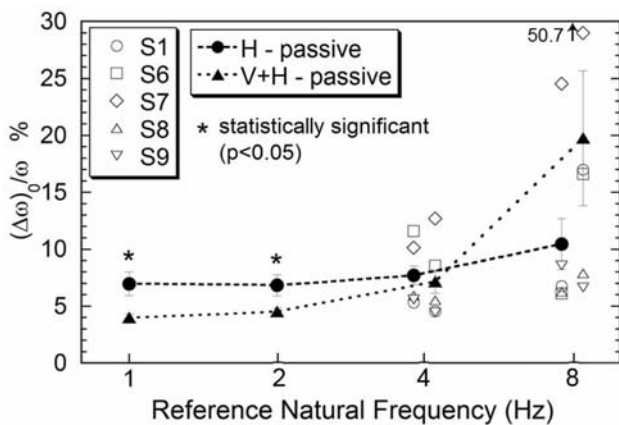


Fig. 5. Weber fractions (in %) for natural frequency obtained at 1 Hz, 2 Hz, 4 Hz, and 8 Hz reference natural frequencies in the haptic only (H) and visual and haptic combined (V + H) passive conditions. Error bars represent the standard error. Also shown are mean WF for five participants at 4 Hz and 8 Hz frequencies, with data points shifted along the abscissa for clarity.

present work serves to define these discrimination thresholds while also comparing results in the passive perception mode with the previous literature. The present study showed no significant difference in WF between the active and passive excitation modes at low frequency (1 and 2 Hz) for each sensory feedback condition, indicating that the thresholds were independent of excitation mode. An exception was for the WFs at 1 Hz frequency with visual only feedback, where the WFs were significantly higher in active mode than in passive mode. This could be due to a large variability in WFs among participants in the active mode. Another possibility could be that with visual only feedback, the discrimination sensitivity is affected by the excitation mode and the present data at 2 Hz are not sufficient to show the differences.

Second, the study compared discrimination ability for varying sensory feedback modality: visual only (V), haptic only (H), and visual and haptic combined (V + H). In the passive excitation mode at 1 Hz and 2 Hz, the data showed significant differences in WF between the H and V + H conditions. No significant differences were observed in the WF between the V and V + H conditions or between the V and H conditions. In contrast, for the active excitation mode, the thresholds between the three feedback conditions failed to show any significance at a 2 Hz reference frequency, while at a 1 Hz reference frequency, WFs were greater in V conditions. Large variability in WF was observed across participants with V feedback in the active mode. For example, for active excitation with V feedback, the average WFs (in %) ranged from 3.2% to 15.9% at 1 Hz, and at 2 Hz, the range of WFs was 3.4% to 11.5%. The variability in the estimated WFs was relatively small for the H and V + H feedback conditions at 1 Hz and 2 Hz. Despite the variability across participants, it can be suggested that visual feedback alone, compared to combined visual and haptic feedback, is sufficient to discriminate natural frequencies of the virtual dynamic system when participants passively interact with the system. When they actively excite the system, haptic-only or visual-only feedback is sufficient. This conclusion contradicts the results reported by Huang et al. [10] for a similar resonance dynamic task, where the authors reported that performance with V + H feedback improved significantly compared to performance with V or H feedback presented alone. Thus, combining the two feedback modalities may improve the human's performance in the skilled task but may not change their sensitivity to task dynamics, such as the natural frequency.

The third factor in the present study was reference natural frequency. In the passive perception mode, results showed no significant effect of reference natural frequency on WF when only haptic cues were presented to the participant's hand. The thresholds followed Weber's law in the 1 Hz to 8 Hz frequency range with an average WF of 8%. This finding was consistent with previous studies in which the frequency WF of motional waveforms was independent of frequency at similar amplitude levels [20]. The four reference natural frequencies likely excited the same mechanoreceptive system that is sensitive in the low-frequency region. Bolanowski et al. [25] showed that the perception of low-frequency stimulation (< 10 Hz) on the lower part of the palm (thenar eminence) is mediated by non-Pacinian (NPI and NPIII) psychophysical channels, however, the stimuli of the present study may also have

excited joint, muscle, and other kinesthetic mechanoreceptors [14]. When both visual and haptic combined cues were presented simultaneously, the WFs increased as the reference natural frequency increased to 8 Hz. Large variation was observed in the frequency WF of 8 Hz with V + H feedback (standard error of 5.92%, see Fig. 5). Different strategies were used by the participants with this combined feedback condition. For example, the WFs for S8 and S9 were not affected by the additional feedback, indicating that these participants were integrating visual and haptic cues, whereas, S1, S6, and S7 performed poorly. Participants commented that for the 8 Hz V + H conditions, the visual cue was not providing additional information and at times distracted their attention from noticing a difference in natural frequency via the haptic channel.

An interesting observation in the present study was that as the reference natural frequency increased from the 1-2 Hz range to the 4-8 Hz range, the thresholds with V + H feedback became similar to that with H feedback. This could be due to the limited bandwidth of smooth pursuit and saccadic eye movements and our poor capability to discriminate 4 Hz and 8 Hz natural frequency movements through the visual sensory mechanism [26]. Thus, at higher frequencies, the haptic sensory system seems better at identifying dynamic system response than the oculomotor mechanism. In the active perception mode, the WFs did not change significantly with varying reference natural frequency. One possible reason could be that the range of the reference frequency in the present study was relatively small to allow manual excitation within the achievable range for human manual control [27], [28]. We limited the active excitation conditions to 1 Hz and 2 Hz reference natural frequencies so that participants could easily achieve the motions necessary to excite the virtual system at its resonant frequency.

The magnitude of forces perceived by human users depends on the magnitudes of the physical parameters constituting a second-order dynamic system. The natural frequency of a dynamic system is derived from the parameters, namely, inertia of the mass and stiffness of the spring. Either the inertia or the stiffness, or both, can influence the natural frequency of the dynamic system. Previous studies have extensively explored WFs for spring stiffness (equivalent to force divided by displacement or simply the inverse of compliance) and inertia (equivalent to force divided by acceleration). The reported WF for stiffness is about 23% [15], [16] and that for inertia is about 21% [11]. These WFs are relatively larger than the reported WFs for force and displacements, which are in the 6%-8% range [12], [13], [29], [30]. Since humans possess no inertia-specific or stiffness-specific "sensors" in the peripheral sensory organs, the reported data is evidence of a loss of sensory resolution when force and displacement cues are combined. The natural frequency of the system, on the other hand, defines the temporal behavior associated with the period of force and displacement oscillations, and human receptor systems possess frequency dependant tuning characteristics [25]. In the present study, the average natural frequency WF with haptic-only feedback is in the 6%-10% range, which is similar to the force/displacement WF and the frequency WF [20]. Thus, unlike inertia and stiffness discrimination, perceptual

resolution persists in the discrimination of natural frequency, where the discrimination task requires sensing of temporal sequences of force and displacement cues.

The discrimination thresholds obtained in the present study are tied to a human's ability to identify the key control parameters of a virtual second-order dynamic system. The physical parameters of the system (mass and stiffness) can be altered while maintaining the behavioral characteristics (natural frequency) of the system. Changing the physical parameters (while keeping natural frequency constant or allowing it to vary) results in different interaction forces exerted on the handle of the haptic device. In order to eliminate any dependency on force magnitude cues for the natural frequency discrimination task, two equivalent systems with different mass and stiffness but equal natural frequency were introduced in the experiments. Thus, the same reference natural frequency is rendered with two distinct physical parameter sets, resulting in distinct interaction force profiles. In [24], Rinker et al. suggest that participants might be using the so called intensity perception as a basis of frequency discrimination. Similarly, in [15], Tan et al. showed that their participants used force and work cues in compliance (inverse of stiffness) discrimination. Tan et al. came to this conclusion by observing significant bias in their task as a function of finger displacement. If intensity perception is the strategy used in the present study, a large bias value would result if the participants tended to vote for a "higher" frequency when the maximum force rendered through the task dynamics was larger. However, there exists no significant bias in the present study, indicating that the participants are equally as likely to select the lower intensity (lower force) set of parameters as they are for the higher intensity set. Thus, the participants in this study are not using maximum force cues to discriminate natural frequency for the virtual second-order dynamic system.

We plan to use the results of this study to design more intelligent shared control and haptic guidance algorithms to improve training effectiveness and efficiency for rhythmic manual control tasks. For example, the WFs determined here can guide progressive training routines that adjust assistance gains incrementally [31]. The findings indicate that haptic feedback, combined with visual feedback, can improve discrimination thresholds for low-frequency dynamic systems perceived passively, while discrimination of the dynamic behavior of actively excited systems does not show sensitivity to feedback modality. This finding will influence shared controller design depending on the approach selected (e.g., record and replay methods that require passive excitation [32], [33], [34] versus virtual fixtures or active shared controllers that require active excitation [4], [5], [7], [8], [31], [35], [36]). The method of excitation alone does not show a significant effect on discrimination ability. We varied the reference natural frequency to determine if different psychophysical channels may be employed depending on the natural frequency of the controlled system but conclude that subjects are likely using the same mechanoreceptive system for the range tested here. Therefore, within the bandwidth of human motor control [27], [28], a consistent haptic guidance paradigm should suffice.

5 CONCLUSIONS

This paper has presented a study of natural frequency WF for virtual second-order dynamic systems. A one degree-of-freedom haptic device was used to investigate human discrimination abilities in active (user excitation) and passive (device excitation) perception modes at 1, 2, 4, and 8 Hz reference natural frequencies. The average WFs are in the 4%-20% range and are dependent on the reference natural frequency and modality of sensory feedback. The data also suggest that the WFs are not affected by the participant's excitation mode. In the passive perception mode, WFs are smallest with combined visual and haptic feedback at 1 Hz and 2 Hz reference frequencies, while WFs are not affected by the modality of sensory feedback in the active perception mode. At 4 Hz and 8 Hz reference natural frequencies, sensory feedback does not show a significant effect on discrimination performance implying a superiority of the haptic sensory system in resolving high-frequency movements. In the frequency range tested in this study, the discrimination thresholds obey Weber's law for haptic only cues presented on passive hand but not with haptic and visual cues combined. This variation in WF highlights the two observed performance trends among participants; one that shows an ability to integrate the two feedback modalities and another that indicates interference with the perception of two feedback modalities. Analysis of the bias at each experimental run indicates that the WFs were in general not affected by varying force and displacement cues in trials due to different system parameter sets. The study provides knowledge of the influence of sensory feedback modality and excitation mode on the human's ability to discriminate the dynamic behavior of manually excited systems. With this information, we seek to design haptic guidance and shared control schemes that demonstrate improved efficacy compared to current approaches for the training of dynamic manual control tasks.

APPENDIX

Rendered force and displacement profiles. Typical forces rendered at the handle and displacement profiles of the handle and cart are plotted at each reference natural frequency and in two excitation modes in order to analyze the effects of all four mass and spring stiffness combinations. Fig. 6 shows the profiles at the 1 Hz reference natural frequency, while a participant holds the handle of the device. Panels on the top are for the passive excitation mode, where the external system excites the handle, and the bottom panels are for the active excitation mode, where the participant excites the handle. Figs. 6a and 6d show rendered forces, and Figs. 6b, 6c, 6e, and 6f show handle and cart displacement profiles, respectively. Each panel shows four profiles corresponding to the four possible mass-stiffness combinations. Solid line profiles are for $k = 35$ N/m, and dashed line profiles are for $k = 25$ N/m. Light and heavy weight lines are for lower (1 Hz) and higher (1.15 Hz) natural frequencies, respectively. In the passive excitation mode, the force profiles show steady decaying patterns and overlapping profiles of similar natural frequency. In the active mode, nonstationary force profiles are due to input handle displacement from the human user. A quantitative analysis of profile amplitudes in the passive excitation mode shows that the rendered force

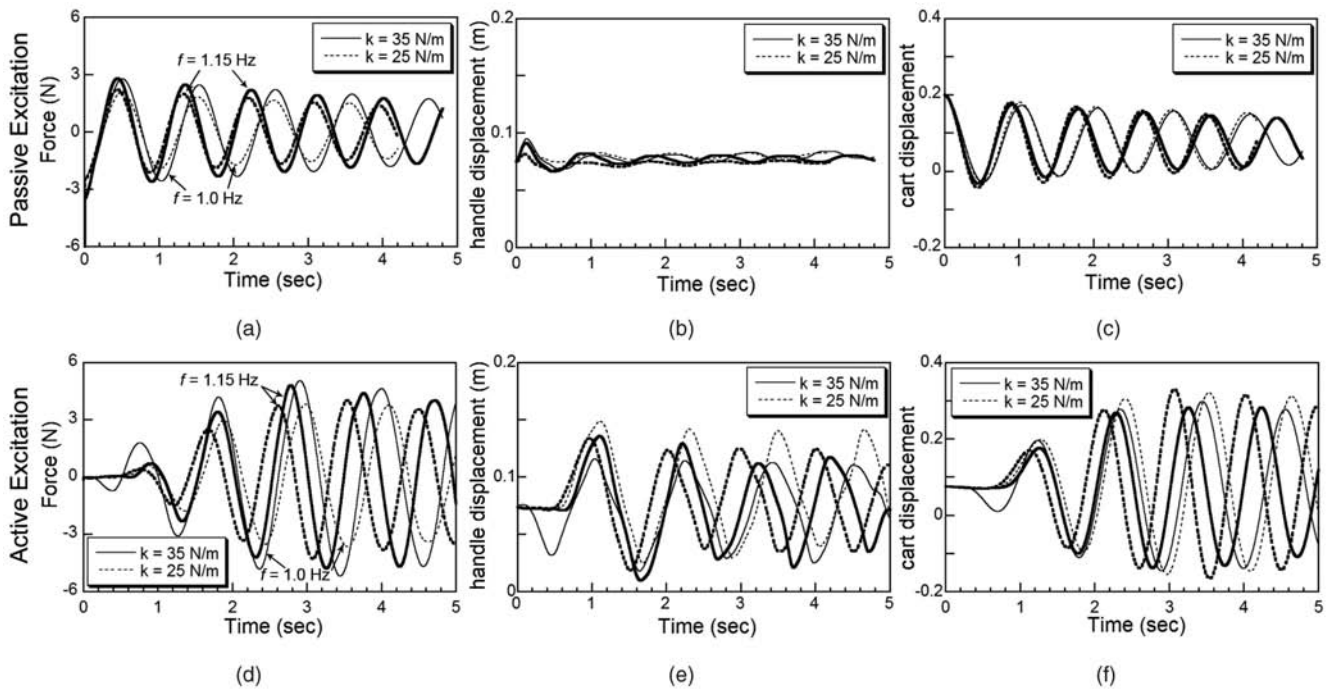


Fig. 6. Typical rendered force and handle and cart displacement profiles at 1 Hz reference natural frequency in (a), (b), (c) passive and (d), (e), (f) active modes.

amplitudes are in the range 3.1 N (at 1 Hz) to 5.5 N (at 4 Hz), and the handle displacement amplitudes are in the 3.9-mm (at 2 Hz) to 6.7-mm (at 4 Hz) range. In order to quantify parasitic effects in the system, viscous and Coulomb friction effects were estimated to be 1.27 Ns/m and 0.24 N, respectively. In the worst case, the ratio of rendered to parasitic forces is 11 percent at 8 Hz.

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REFERENCES

- [1] K.M. Lynch and M.T. Mason, "Dynamic Nonprehensile Manipulation: Controllability, Planning, and Experiments," *Int'l J. Robotics Research*, vol. 18, no. 1, pp. 64-92, 1999.
- [2] R.J. Jagacinski and J.M. Flach, *Control Theory for Humans: Quantitative Approaches to Modeling Performance*. Lawrence Erlbaum Assoc., p. 91, 2003.
- [3] D. Sternad, M. Duarte, H. Katsumata, and S. Schaal, "Bouncing a Ball: Tuning into Dynamic Stability," *J. Experimental Psychology: Human Perception and Performance*, vol. 27, no. 5, pp. 1163-1184, 2001.
- [4] M.K. O'Malley, A. Gupta, M. Gen, and Y. Li, "Shared Control in Haptic Systems for Performance Enhancement and Training," *ASME J. Dynamic Systems, Measurement and Control*, special issue on novel robotics and control, vol. 128, no. 1, pp. 75-85, 2006.
- [5] J.L. Patton and F.A. Mussa-Ivaldi, "Robot-Assisted Adaptive Training: Custom Force Fields for Teaching Movement Patterns," *IEEE Trans. Biomedical Eng.*, vol. 51, no. 4, pp. 636-646, 2004.
- [6] J.L. Patton, F.A. Mussa-Ivaldi, and W.Z. Rymer, "Altering Movement Patterns in Healthy and Brain-Injured Subjects via Custom Designed Robotic Forces," *Proc. 23rd Ann. Int'l Conf. IEEE Eng. in Medicine and Biology Soc. (EBMC '01)*, pp. 1356-1359, 2001.
- [7] J.L. Emken and D.J. Reinkensmeyer, "Robot-Enhanced Motor Learning: Accelerating Internal Model Formation During Locomotion by Transient Dynamic Amplification," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, vol. 13, no. 1, pp. 33-39, 2005.
- [8] Y. Li, V. Patoglu, and M.K. O'Malley, "Negative Efficiency of Fixed Gain Error Reducing Shared Control for Training in Virtual Environments," *ACM Trans. Applied Perception*, vol. 6, no. 1, 2009.
- [9] J.B. Dingwell, C.D. Mah, and F.A. Mussa-Ivaldi, "Manipulating Objects with Internal Degrees of Freedom: Evidence for Model-Based Control," *J. Neurophysiology*, vol. 88, no. 1, pp. 222-235, 2002.
- [10] F.C. Huang, R.B. Gillespie, and A.D. Kuo, "Visual and Haptic Feedback Contribute to Tuning and Online Control During Object Manipulation," *J. Motor Behavior*, vol. 39, no. 3, pp. 179-193, 2007.
- [11] G.L. Beauregard, M.A. Srinivasan, and N.I. Durlach, "The Manual Resolution of Viscosity and Mass," *Proc. ASME Dynamic Systems and Controls Division (DSCD '95)*, vol. 57, pp. 657-662, 1995.
- [12] E.E. Brodie and H.E. Ross, "Sensorimotor Mechanisms in Weight Discrimination," *Perception and Psychophysics*, vol. 36, no. 5, pp. 477-481, 1984.
- [13] L.A. Jones, "Matching Forces: Constant Errors and Differential Thresholds," *Perception*, vol. 18, no. 5, pp. 681-687, 1989.
- [14] F.J. Clark and K.W. Horch, "Kinesthesia," *Handbook of Perception and Human Performance: Cognitive Processes and Performance*, vol. 1, K.R. Boff, L. Kaufman, and J.P. Thomas, eds., pp. 13/1-13/62, John Wiley & Sons, 2008.
- [15] H.Z. Tan, N.I. Durlach, G.L. Beauregard, and M.A. Srinivasan, "Manual Discrimination of Compliance Using Active Pinch Grasp: The Roles of Forces and Work Cues," *Perception and Psychophysics*, vol. 57, no. 4, pp. 495-510, 1995.
- [16] L.A. Jones and I.W. Hunter, "A Perceptual Analysis of Stiffness," *Experimental Brain Research*, vol. 79, no. 1, pp. 150-156, 1990.
- [17] L. Nicholson, R. Adams, and C. Maher, "Reliability of a Discrimination Measure for Judgments of Non-Biological Stiffness," *Manual Therapy*, vol. 2, no. 3, pp. 150-156, 1997.
- [18] L. Jones, I. Hunter, and S. Lafontaine, "Viscosity Discrimination: A Comparison of an Adaptive Two-Alternative Forced-Choice and an Adjustment Procedure," *Perception*, vol. 26, no. 12, pp. 1571-1578, 1997.
- [19] L.A. Jones and I.W. Hunter, "A Perceptual Analysis of Viscosity," *Experimental Brain Research*, vol. 94, no. 2, pp. 343-351, 1993.
- [20] A. Israr, H.Z. Tan, and C.M. Reed, "Frequency and Amplitude Discrimination along the Kinesthetic-Cutaneous Continuum in the Presence of Masking Stimuli," *J. Acoustical Soc. Am.*, vol. 120, no. 5, pp. 2789-2800, 2006.

- [21] D. Morris, H.Z. Tan, F. Barbagli, T. Chang, and K. Salisbury, "Haptic Feedback Enhances Force Skill Learning," *Proc. Second Joint EuroHaptics Conf. and 2007 Symp. Haptic Interfaces for Virtual Environment and Teleoperator Systems (World Haptics '07)*, pp. 21-26, 2007.
- [22] N.A. Macmillan and C.D. Creelman, *Detection Theory: A User's Guide*, second ed., pp. 3-48. Lawrence Erlbaum Assoc., 2004.
- [23] R. Littell, W.W. Stroup, and R. Freund, *SAS for Linear Models*, fourth ed., pp. 33-90. Wiley Publishers, 2002.
- [24] M.A. Rinker, J.C. Craig, and L.E. Bernstein, "Amplitude and Period Discrimination of Haptic Stimuli," *J. Acoustical Soc. Am.*, vol. 104, no. 1, pp. 453-463, 1998.
- [25] S.J. Bolanowski, G.A. Gescheider, R.T. Verrillo, and C.M. Checkosky, "Four Channels Mediate the Mechanical Aspects of Touch," *J. Acoustical Soc. Am.*, vol. 84, no. 5, pp. 1680-1694, 1988.
- [26] P.E. Hallett, "Eye Movements," *Handbook of Perception and Human Performance: Cognitive Processes and Performance*, vol. 1, K.R. Boff, L. Kaufman, and J.P. Thomas, eds., pp. 10/1-10/112, John Wiley & Sons, 1986.
- [27] E. Kunesch, F. Binkofski, and H.-J. Freund, "Invariant Temporal Characteristics of Manipulative Hand Movements," *Experimental Brain Research*, vol. 78, no. 3, pp. 539-546, 1989.
- [28] R.N. Stiles, "Acceleration Time Series Resulting from Repetitive Extension Flexion of the Hand," *J. Applied Physiology*, vol. 38, no. 1, pp. 101-107, 1975.
- [29] X.D. Pang, H.Z. Tan, and N.I. Durlach, "Manual Discrimination of Force Using Active Finger Motion," *Perception and Psychophysics*, vol. 49, no. 6, pp. 531-540, 1991.
- [30] L.A. Jones, I.W. Hunter, and R.J. Irwin, "Differential Thresholds for Limb Movement Measured Using Adaptive Techniques," *Perception and Psychophysics*, vol. 52, no. 5, pp. 529-535, 1992.
- [31] Y. Li, J.C. Huegel, V. Patoglu, and M.K. O'Malley, "Progressive Shared Control for Training in Virtual Environments," *Proc. Third Joint Eurohaptics Conf. and Symp. Haptic Interfaces for Virtual Environments & Teleoperator Systems*, 2009.
- [32] R.B. Gillespie, M.S. O'Modhrain, P. Tang, D. Zaretzky, and P. Cuong, "The Virtual Teacher," *Proc. ASME Int'l Mechanical Eng. Congress and Exposition (IMECE '98)*, pp. 3354-3361, 1998.
- [33] K. Henmi and T. Yoshikawa, "Virtual Lesson and Its Application to Virtual Calligraphy System," *Proc. IEEE Int'l Conf. Robotics and Automation (ICRA '98)*, pp. 1275-1280, 1998.
- [34] Y. Yokokohji, R.L. Hollis, T. Kanade, K. Henmi, and T. Yoshikawa, "Toward Machine Mediated Training of Motor Skills-Skill Transfer from Human to Human via Virtual Environment," *Proc. IEEE Int'l Workshop Robot and Human Comm. (RO-MAN '96)*, pp. 32-37, 1996.
- [35] A. Bettini, P. Marayong, S. Lang, A.M. Okamura, and G.D. Hager, "Vision-Assisted Control for Manipulation Using Virtual Fixtures," *IEEE Trans. Robotics*, vol. 20, no. 6, pp. 953-966, 2004.
- [36] P.G. Griffiths and R.B. Gillespie, "Sharing Control between Humans and Automation Using Haptic Interface: Primary and Secondary Task Performance Benefits," *Human Factors*, vol. 47, no. 3, pp. 574-590, 2005.
- [37] Y. Li, A. Israr, V. Patoglu, and M.K. O'Malley, "Passive and Active Perception Just Noticeable Difference for Natural Frequency of Virtual Dynamic Systems," *Proc. IEEE 16th Symp. Haptic Interfaces for Virtual Environments and Teleoperator Systems (HAPTICS '08)*, pp. 25-31, 2008.



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