Progressive Haptic and Visual Guidance for Training in a Virtual Dynamic Task

Joel C Huegel*
Department of Mechatronic Engineering and Electronic Engineering
ITESM - Guadalajara Campus
Zapopan, Jalisco
Mexico

Marcia K O'Malley†
Mechanical Engineering and Materials Science Department
Rice University
Houston, TX 77005

Abstract

This paper presents the design and implementation of a novel progressive haptic guidance scheme and a similar visual guidance scheme for acquisition of a dynamic motor skill. The paper compares the schemes' performance to each other and to practice alone without any form of guidance. The target-hitting task is represented in a visual and haptic virtual environment and implemented in a training protocol that lasts eleven sessions over a two-month period. The progressive guidance controller employs as inputs two expertise-based performance measures, trajectory error and input frequency. The analysis of the experimental results demonstrates that while guidance is active, haptic guidance outperforms both visual guidance and practice alone (no guidance) until late in the protocol when all three groups saturate at the same level of performance. The results fail to show significant differences in training outcomes because the performance of all participants saturates toward the end of the protocol. The key implication of the experimental findings is that visual and haptic guidance presented in a progressive manner have no detrimental effects on performance. Our results confirm that haptic guidance, based on skill component measures, is effective early in the training protocol when participants are only beginning to understand the components of the task but should be progressively removed to avoid possible negative dependence on the guidance.

Index Terms: H.1.2 [Model and Principles]: User/Machine Systems—human factors H.5.2 [Information Interfaces and Presentation]: User Interfaces—Haptic I/O, evaluation/methodology, training help and documentation

1 Introduction

Haptics-enabled virtual environment (VE) technologies are used for skill training applications in such areas as vehicle control, medical procedures, sports training and rehabilitation [2, 6, 10, 20]. These technologies provide reliable data acquisition, analysis, feedback, and evaluation of motor skill task performance while simultaneously providing a comparatively low-cost and low-risk training platform. Virtual environments used for training intend to reduce risk, improve and accelerate skill acquisition over traditional training schemes, and transfer what is learned in the simulation environment to the equivalent or targeted real world task. Virtual training environments (VTEs) are implemented either to provide an environment for practice that is as similar as possible to the real task or to act as an assistant by augmenting the feedback in some way during training. Commercial examples of these augmented systems include heads up displays (HUDs) for pilots and simulators for surgery residents [17, 24].

Haptic feedback can play an important role both in improving the fidelity of the training environment and in providing augmentation during training. Various haptics-enabled virtual training schemes have been proposed. One scheme is to first present the performance of an expert (human or robotic) to a trainee via visual and haptic feedback and then allow the trainee to practice the task unassisted [11] [23]. A second approach requires the trainee to perform the task with enforced restrictions or reductions of the degrees of freedom of the task as proposed by Bernstein and more recently implemented as *virtual fixtures* by Rosenberg et al. and Abbott et al. [1, 5, 21]. A third approach, shared control, modifies the dynamics of the system so as to encourage the correct behavior from the trainee [7, 10, 18]. A comparative study of these last two approaches was performed by Srimathveeravalli et al. showing slightly better performance from the shared control approach over the virtual fixture approach [22]. Despite the current use of VTE's, the measurable benefits of haptically augmented VTE's over real or virtual practice in dynamic task training have not been clearly demonstrated.

When guidance is provided on the same sensory channel as the skill training that is sought – in this case the haptic channel – dependence or interference can occur. The trainee actually learns the dynamics of the augmented system rather than the targeted system. In early attempts to use haptics for training, such as the *record and play* strategies, the dynamics of an expert performing the task are recorded and are then played back to the novice to assist learning. The record and replay training scheme does not account for differences due to user-specific dynamics and restricts the novice to the expert performance without consideration of possible alternate strategies for completing the task. Results from studies on record and replay effectiveness for motor skill training are highly inconclusive [8, 9, 11, 25]. In an attempt to overcome the deficiencies of the record and replay model, Bayart et al. proposed a four-step scheme similar to the stages in learning to ride a bicycle [3]. In Bayart's implementation the stages were fixed and had to be switched manually, thereby preventing a truly *progressive* scheme. Ideally the progressive model should adapt to the current performance of the participant and gradually diminish as performance improves and vice versa. Bell et al. showed benefits from a performance-based progressive guidance scheme for self-learning of a radar-tracking task but they limited the length of "training" to one session [4]. In a robot-assisted rehabilitation simulation, Reinkensmeyer et al. measured adaptation to a dynamic environment via trajectory error [19]. The control gains of the guidance robot were then adjusted at each trial based on the error. The simulation results suggest that providing guidance only when needed is more effective than a fixed amount of assistance. To test Reinkensmeyer's hypothesis, Li et al. first compared a fixed-gain shared control scheme

*e-mail: jhuegel@itesm.mx
†e-mail:omalleym@rice.edu

IEEE Haptics Symposium 2010
25 - 26 March, Waltham, Massachusetts, USA
978-1-4244-6822-5/10/$26.00 ©2010 IEEE

to practice alone (no guidance) in a dynamic target-hitting task (similar to the one implemented in our study) and showed that the fixed-gain scheme had negative efficacy both during and after guidance [16]. Then, Li et al. compared a progressive shared control scheme to the same fixed-gain scheme and showed significant improvement over fixed-gain guidance, but no significant differences from practice alone with either the guidance active or inactive [15]. They alluded to the need to design the guidance scheme based on the significant components of the task.

In this paper, we design, implement, and demonstrate progressive haptic and visual guidance schemes for training in a non-trivial dynamic task where the amount of guidance is controlled by decreasing gain algorithms that utilize measures of performance in skill components as inputs. We explore the role of guidance and the sensory channel on which it is displayed. This progressive guidance scheme was proposed in our prior work where we recognized that the guidance must be based on measures of performance that are derived from the key skill components required for success in the task [13]. In that paper we analyzed performance data obtained from Li's VTE and found two primary skill components and concluded that two measures, trajectory error and input frequency, could be used as inputs for a guidance controller for the task at hand [13].

This paper is organized as follows: Section 2 presents the methods used including the apparatus and VTE, task description, experiment design, guidance schemes to be implemented, participant description and data analysis. Section 3 presents the results while Section 4 discusses the findings and contributions. Section 5 draws the conclusions of this experiment.

2 Methods

A training experiment was conducted over two months to investigate and compare the proposed haptic and visual guidance schemes to practice alone (no guidance). The participant training was performed in a VTE dynamic task as shown in Fig. 1. The duration of the training experiment was eleven sessions.

2.1 Apparatus and Virtual Environment

The experimental setup, illustrated in Fig. 1, is comprised of a nineteen inch LCD video display and a two degree of freedom (DOF) force feedback joystick (Immersion IE2000). The visual feedback control loop rate operates at 58Hz while the haptic feedback is controlled and displayed at 1 kHz on a 2GHz computer. The states of the dynamic system are recorded to a data file at 50Hz. The chosen virtual environment is a second order system modeled as two point masses connected by a spring and damper in parallel. This two-mass system has four degrees of freedom, namely the planar motion of each of the point masses, m_1 and m_2. Therefore, it is under-actuated since the only control inputs are the planar motions of m_1, corresponding to the joystick position. All participants receive visual feedback of the targets and moving masses via the LCD display. Additionally, all participants receive haptic feedback from the VTE in the form of the force interactions of the dynamic system described by the following equations of motion:

$$Fs_x = m_2\ddot{x} + b_s\dot{x} + k_s x \tag{1}$$

$$Fs_y = m_2\ddot{y} + b_s\dot{y} + k_s y \tag{2}$$

where Fs_x and Fs_x are the forces generated by the system dynamics, b_s is the damping, and k_s is the spring constant of the modeled second-order system (m_2 =5 Kg, b_s =1 Ns/m, and k_s = 80 N/m) The total force computed and delivered to the motor controllers for display on the haptic device is computed by the following sum:

$$F_D = \sum(F_h + F_s) \tag{3}$$

where F_h is the force applied by the participant's hand and F_s are the forces generated by the system dynamics. The experimental setup includes physical blinders around the test site to mitigate visual distractions. During all trials, all participants wear noise cancelling headphones playing pink noise loud enough to mitigate interference from audio cues such as the physical environment and movement sounds of the joystick during the execution of the experimental task.

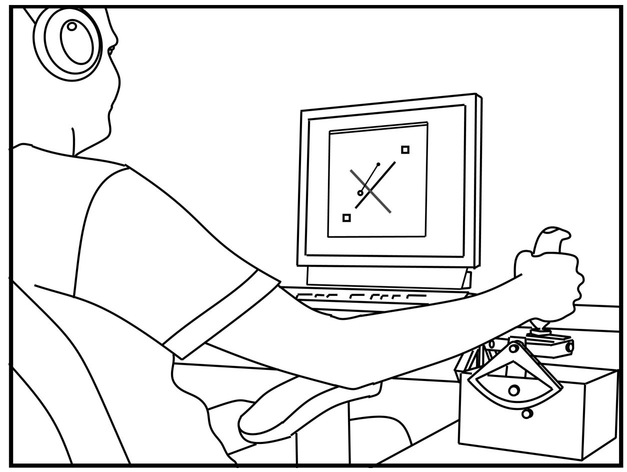


Figure 1: A participant is sitting at the virtual training environment. The interface includes a visual feedback display and a haptic joystick for force feedback, both of which provide feedback of the system dynamics to all trainees regardless of guidance scheme.

2.2 Task Description

The task, illustrated in Fig. 2, was to manipulate the motion of the point mass m_1 via the 2-DOF haptic joystick, and thus indirectly, through the system dynamics, control the object (m_2) to hit as many of the diagonally placed targets as possible during each 20-second long trial. The targets were located 10 cm apart on the visual display representing 76 degrees of joystick rotation. Once a target was acquired, the current target became inactive and the opposite target became active and so forth. All participants, regardless of the guidance received, experienced the visual and haptic feedback of the dynamics of the system in the VTE.

2.3 Experiment Design

In order to compare the effects of training with haptic or visual guidance to practice alone (no guidance) the experiment design consisted of one evaluation session, followed by nine training sessions (two or three sessions per week), and one retention session after 30 days for a total of eleven sessions as shown in Fig. 3. The nine training sessions were spaced two to five days apart. The retention session was at least 30 days but no more than 45 days after the last training session. Sessions were one of the factors of the experiment. Each training session contained three subsessions: first, a pre-guidance baseline with five trials; second, a guidance subsession with fifteen trials; and third, a post-guidance baseline again with five trials. Each trial lasted 20 seconds for a total duration of approximately nine minutes baseline and guidance training time per session. Participants were specifically instructed to acquire as many targets as possible in each 20 second trial. Each trial began with the two point masses 0.1 mm apart at the center of the screen and ended at precisely 20 seconds from the start signal. Between each subsession participants filled out a small on-line questionnaire that took approximately three minutes to complete. At the end of each training session, all participants filled out a paper questionnaire self-evaluating the daily performance. Thus the total time re-

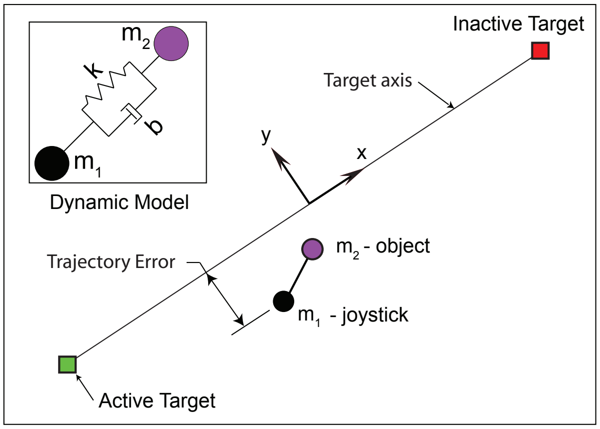


Figure 2: Target hitting task: the participant controls the location of m_1 (force feedback joystick) in order to cause m_2 (object) to hit the active target. Inset shows the virtual underactuated system. Trajectory error is defined as the deviation of m_1 (object) from the target axis (adapted from [15]).

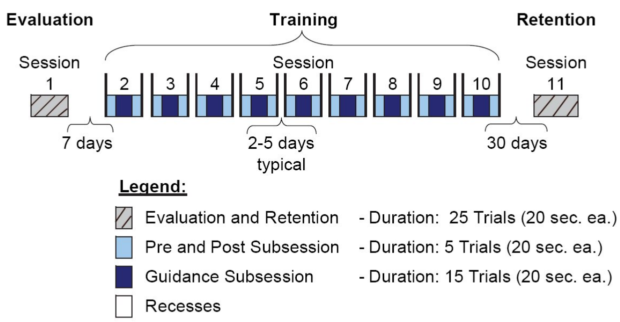


Figure 3: Training experiment design: consists of eleven sessions including one evaluation session and one retention session as shown. During guidance subsessions, the haptic and visual groups received the corresponding progressively diminishing guidance. During pre- and post-guidance subsessions no group received guidance. Rest periods between sessions are indicated with braces.

quired was 16 to 20 minutes per participant per session for a total of under four hours over the two-month period.

The objective of the task was for the participant to hit as many targets as possible in each 20 second trial. A hit was registered whenever the center position of the object (m_2) was detected to be within 4 mm of the active target center. We define hit count (n_{hit}), the objective measure of performance, as the number of target hits occuring in each trial.

2.4 Guidance Schemes

In prior work, we showed that there exist two skill components required for success in this task [13]. First, the participant should excite the system close to its resonant frequency in order to generate rhythmic oscillations of the object (m_2). Second, the participant should not deviate from the target axis so as to ensure that the object (m_2) passes through the targets. The task design does not require the object (m_2) to stop at the target location but rather just to pass through the target. In addition to the measure of hit count presented to the participants as the objective of the task, we proposed two measures of performance of the two primary skill components and suggested that they could be used as inputs to a progressive guidance controller [13].

Thus we defined trajectory error (e_{traj}) as the absolute magnitude of the deviation (y direction as shown in Fig. 2) of the input joystick position (m_1) at each sampled instant (50Hz sample rate) summed for the entire trial (n), and is expressed in units of millimeters. Mathematically,

$$e_{traj} = \sum_{i=1}^{n} abs(y_i) \tag{4}$$

where y_i is the deviation of one sample.

Based on the observation of the importance of input excitation frequency for this task, input frequency (f_{input}) is a measure of the rhythmic performance in a trial. To compute f_{input} we take the fast Fourier transform (FFT) of the position data of the joystick (m_1). The FFT power spectrum is a convenient way to determine the amplitude and frequency of the motion that is being applied to a system and was used in a similar way by Huang et al. in similar tasks to quantify performance [12]. For clarification, even though the FFT plot is called a "power spectrum," in this particular case it has units of mm^2. To simplify the understanding of the measure, our definition includes a normalizing coefficient. The equation for the second performance measure f_{input} is given in units of (Hz/Hz) as follows:

$$f_{input} = \frac{1}{f_r} \times f(arg(max(FFT))) \tag{5}$$

where f_r is the resonant frequency of the system. Therefore, exciting the system at the resonant frequency will give a value of $f_{input} = 1(Hz/Hz)$ regardless of the system frequency. In this experiment the system parameters are maintained constant so f_r is a constant.

While the participants are explicitly told that hit count, n_{hit}, is the objective measure of performance, e_{traj} and f_{input} measure the participants' performance in the two key skill components of the task. In our analysis in prior work, we showed that these two measures correlate well with hit count but not with each other suggesting independence [13]. This fact drove the design of the guidance scheme for this work to represent the two measures independently and orthogonally.

After completing the initial evaluation session, participants are ranked by n_{hit}. The ranked participants are then randomly assigned to one of three groups: *haptic guidance*, *visual guidance* or *practice alone*. The mean scores of the groups are compared to ensure that the groups are balanced at the beginning of the training protocol. The haptic and visual guidance groups receive a form of guidance during the guidance subsession of each of the nine training sessions. One group receives the guidance haptically while the other receives it visually. The guidance for both is in the form of two orthogonal regions as shown in Fig. 4 as we previously proposed to demonstrate the best performance in the two skill components [14]. The first region (shown in dark gray in Fig. 4) indicates the maximum allowable deviation from the target axis that will still result in a target acquisition, thereby reducing e_{traj}. The location of this region is fixed. The second region (shown in light gray in Fig. 4) oscillates at the resonant frequency of the dynamic system and with an amplitude that, if tracked, will ensure sufficient output amplitude to acquire the targets.

For the visual guidance scheme, the two regions are represented by colored regions whose intensities diminish independently as performance improves in each of the two measures. The regions eventually fade to the background color. Similarly, in the haptic scheme, we represent the edges of the regions with stiff virtual walls for the trajectory error guidance and a PD tracking controller for the input frequency guidance as shown in Fig. 5. The minimum force required to penetrate the walls is progressively reduced as performance improves thus gradually shifting primary control from the

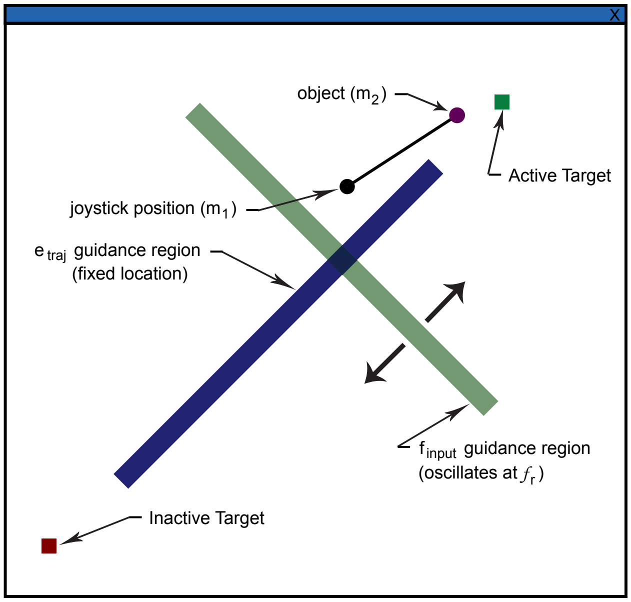


Figure 4: Guidance schemes designed from measures of performance in the dynamic task show both input deviation and frequency task components to the trainees. In addition to a practice alone (no guidance) control group, one group receives progressive guidance only through the visual display while a third group receives equivalent progressive guidance only through the haptic joystick display.

robot to the trainee as the training protocol progresses. Both the visual and haptic guidance schemes employ exponentially diminishing gains that are controlled by the two measures e_{traj} and f_{input} of participant performance in each successive trial. The gains are updated and the corresponding levels of guidance for the two components are presented to the participant in the next trial. In the case of haptic guidance, the calculated guidance forces are combined with the system dynamic forces before being presented to the user at the joystick interface on the haptic channel.

Thus the total force delivered to the motor controllers for display on the haptic device is computed by the following sum:

$$F_D = \sum(F_h + F_w + F_c + F_s) \tag{6}$$

where F_h is the force applied by the participant's hand, F_w is the force created by the virtual wall guidance, F_c is the force created by the PD tracking guidance, and F_s are the forces generated by the system dynamics. The wall force is computed with the following conditionals: if the joystick position is in free space:

$$F_w = 0 \tag{7}$$

if the joystick position is inside the wall:

$$F_w = k_w \tag{8}$$

where k_w is the maximum gain for the wall. Finally, if the joystick is on the wall face within ±0.05mm of the wall centerline, then the following bi-cubic equation is used to compute the wall force:

$$F_w = k_w(2t_w^3 - 3t_w^2) \tag{9}$$

The progression of the guidance diminishes according to the following logic: when three successive trials show improvement in performance in one of the two measures, the corresponding gain

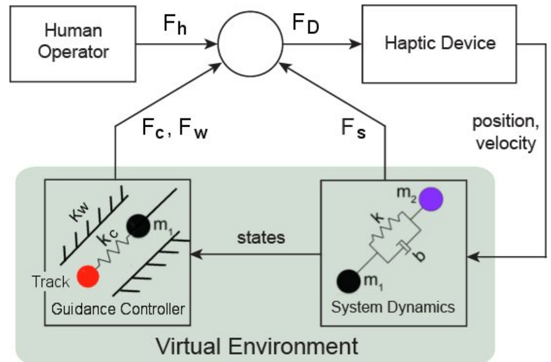


Figure 5: Block diagram of the haptics-enabled virtual training environment with haptic guidance augmentation. The guidance is in the form of virtual walls to mitigate deviation from the target axis and in the form of a PD tracking controller to encourage excitation at the resonant frequency of the system.

decreases. In contrast, when three trials show degrading performance, the gain increases. Fluctuating performance trends cause the gain to remain unchanged. The measures are sensitive enough so as to present an imperceptible amount of change in the guidance at each step yet disappear within three sessions in the presence of excellent performance. Figure 6 shows two typical participant's exponentially diminishing gains with some occasions where the gains remained the same or increased.

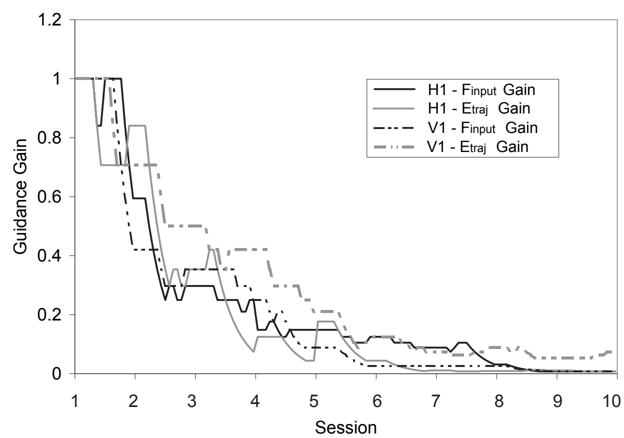


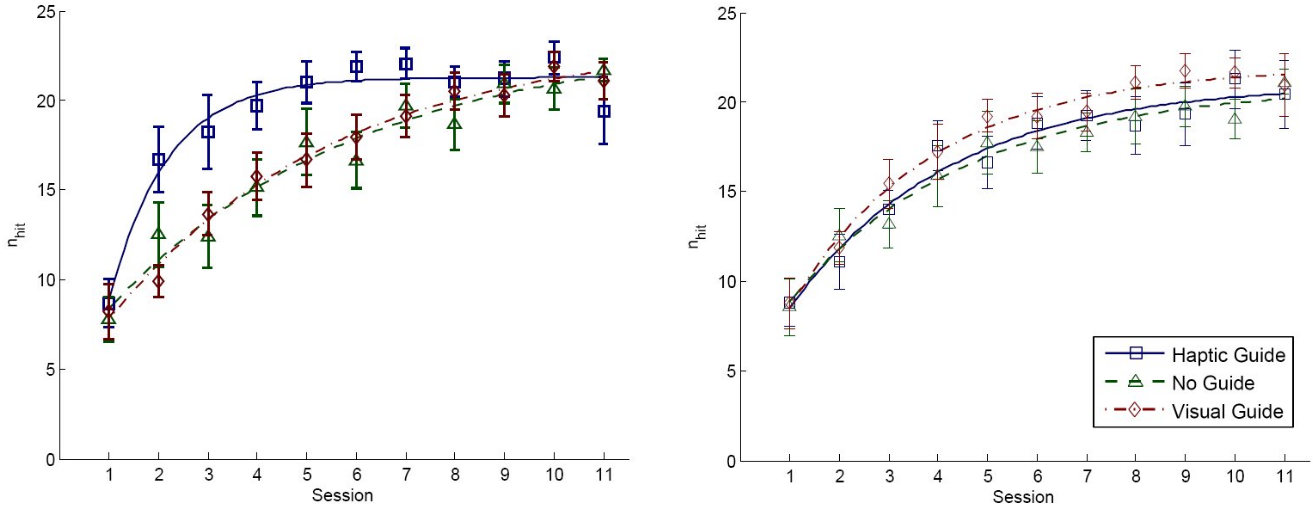
Figure 6: Guidance gains, based on the performance measures e_{traj} and f_{input}, diminish throughout training in the dynamic task for both haptic (H1) and visual (V1) guidance trainees.

2.5 Participants

The experiment involved 24 healthy participants, (7 female and 14 male; 22 right-handed and 2 left-handed; Ages 18 to 51) primarily undergraduate students with no previous experience with haptic devices. A university approved IRB form was used to obtain informed written consent from all participants.

2.6 Data Analysis

For all participants, values for n_{hit} for each subsession are recorded: five trials for pre and post guidance subsessions and fifteen trials for the guidance subsession. Thus each of the 24 participants has five data points (or fifteen during guidance) for each of the eleven



(a) Hit count During Guidance Subsession

(b) Hit count During Post-Guidance Subsession

Figure 7: On the left side is the guidance subsession and on the right side is the post guidance subsession. Hit count (n_{hit}) demonstrates increasing trends across sessions regardless of guidance mode. The guidance subsession shows the faster rate toward saturation of the haptic guidance group.

sessions of training resulting in a total of 1320 observations for pre-guidance and post-guidance subsessions (5 trials, 11 sessions, and 24 participants) or 3960 observations for the guidance subsessions (15 trials, 11 sessions, and 24 participants). The data were also averaged by guidance mode to be fit with exponential curves using MATLAB^{TM} and the best fit curves were determined from the R^2 values.

Sessions are a within-subjects factor (also called *repeated measures* because the measure is repeatedly taken on each participant) since the same subjects were used for all 11 sessions. Guidance mode had three levels namely *haptic guidance, visual guidance*, and *practice alone* and is a between-subjects factor since eight different subjects were used for each one of the guidance modes for a total of 24 participants in the experiment. Thus the experiment is a factorial design with session (11) and guidance mode (3) factors.

An ANOVA cannot be used, since the data fails to have a normal distribution of the residuals. Instead, a Chi-squared automatic interaction detector (CHAID) analysis decision tree highlights significant main effects of session and guidance mode on the dependent performance variable of hit count.

3 Results

The data analysis and results are obtained from the two-month human-user study. A total of 24 participants completed the protocol. Figure 7 shows the performance of the modes (haptic guidance, visual guidance and practice alone) for both the guidance subsession and the post-guidance baseline subsession. The pre-guidance subsessions are not included in the analysis as that data, similar to the post-guidance baseline data, failed to show significant differences in performance between the three guidance modes during those subsessions. The scores of the fifteen guidance trial scores (or five during post-guidance) for the eight participants of each mode are averaged to obtain one mean score in terms of hit count per each subsession. The data points plotted in Fig. 7 represent the mean of the subsession scores of each guidance mode with error bars indicating the standard error of the mean. The n_{hit} scores for all participants show increasing trends across all sessions as training progressed with saturation at about 22 hits per trial.

In order to visualize trends that suggest skill acquisition, power functions are fit to the data according to the following equation:

$$y = -ae^{-bx} + c \tag{10}$$

where a, b, and c are the parameters of the equation and have goodness of fit values in excess of $R^2 = 0.95$ except for the haptic guidance group in the guidance subsession in which n_{hit} had a goodness of fit of $R^2 = 0.86$. The fit curves are also plotted in Fig. 7 along with the mean subsession scores and associated error bars. A summary of the curve fitting results, including estimated parameters and goodness of fit for each of the three groups of participants are shown in Table 1. During both guidance and post guidance subsessions, all guidance modes reached saturation in terms of the hit count.

During the guidance subsession, the haptic group reached saturation at a significantly faster rate than the other two groups (parameter b) as shown in Fig. 7(a). In other words, during the guidance subsession, the haptic guidance mode increases in performance at a faster rate. This performance rate increase, however, is not observed during the postguidance baseline as demonstrated by the data shown in Fig. 7(b).

Figure 8 shows the Chi-squared automatic interaction detector (CHAID) analysis decision tree of the data collected during the guidance subsession. The tree demonstrates the significant effect of session across the eleven sessions. As expected, the initial evaluation session data fails to show significant differences due to the fact that the groups are balanced at that point and guidance has yet to be activated for any participants. The CHAID analysis demonstrates that the haptic guidance mode is significantly different from visual guidance and practice alone (no guidance) during sessions 2 through 8. For sessions 9 through 11 the data again fails to reveal significant differences. The analysis fails to show significant differences between visual guidance and practice alone. A similar CHAID analysis was conducted on the post-guidance subsession data. While the post-guidance data showed significant effects of session, the analysis failed to show significant effects of guidance mode. The analysis of the experimental results via the CHAID test demonstrate that during the guidance subsession, the haptic guidance significantly outperforms both the visual guidance and practice alone (no guidance) in terms of hit count until Ses-

Table 1: Summary of the curve fitting procedures for the hit count measure of each group

	Goodness of fit Guidance		Goodness of fit Post-Guidance	
Guidance Group	R^2	Fit Parameters	R^2	Fit Parameters
Haptic Guidance	0.95	$a = 29.0$, $b = 0.85$, $c = 21.3$	0.96	$a = -17.12$, $b = 0.310$, $c = 21.05$
Non Guidance	0.96	$a = 18.36$, $b = 0.201$, $c = 23.4$	0.97	$a = -16.0$, $b = 0.278$, $c = 20.94$
Visual Guidance	0.99	$a = 19.39$, $b = 0.220$, $c = 23.4$	0.99	$a = -18.9$, $b = 0.343$, $c = 22.0$

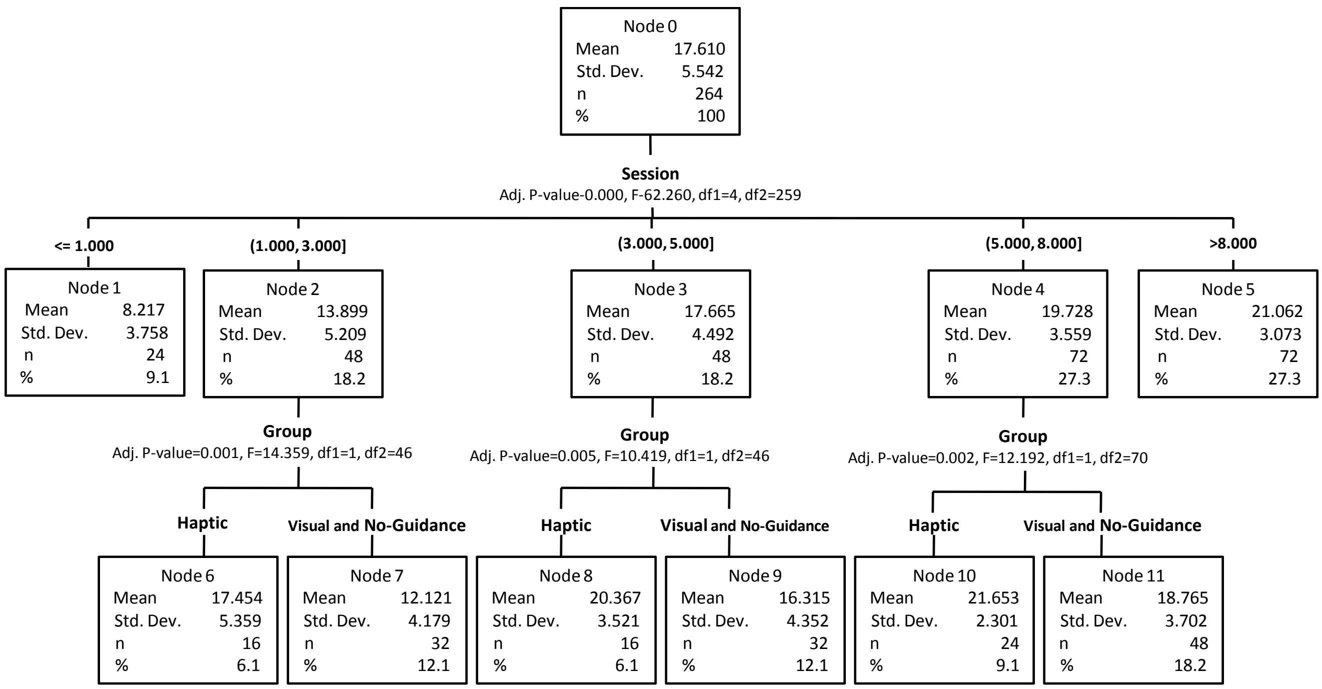


Figure 8: The CHAID analysis decision tree of the guidance subsession demonstrates the significant effects of Session (second row of the tree) and of Guidance Mode groups (third row of the tree). The analysis shows that the haptic guidance group is significantly different from the visual guidance and practice alone (no guidance) groups in sessions 2 through 8.

sion 9. During the post-guidance subsession baseline trials the data fail to show significant differences between the visual, haptic, and practice groups in all sessions.

4 Discussion

This paper presents the implementation of a novel progressive guidance scheme designed to improve the effectiveness of a virtual training environment (VTE) used for motor skill acquisition. The scheme integrates the measurements of key skills as input gains. Depending on the participants performance from trial to trial, the guidance gains progressively diminish, thereby reducing the level of guidance. The results of this methodology confirm prior work that suggested that providing guidance only when needed is more effective than fixed amounts of assistance throughout the training protocol ([15], [7]).

The CHAID analysis shows, as expected, that session is a significant factor thus demonstrating that skill acquisition is occurring from session to session. The trends are approximated well by exponential curves, indicating skill acquisition learning rates. During the guidance subsessions, the haptic guidance mode has the greatest rate of $b = -1.33$ (parameter b of the curve fit) compared to $b = 0.15$, and $b = 0.08$ for visual and no guidance respectively. This higher rate of haptic guidance does not hold during post-guidance subsessions. Rather the data fails to show significant difference between the three groups. Nevertheless, in a similar experiment, Li et al. suggested interference of fixed-gain haptic guidance since its "learning rate" was significantly lower than for practice alone. Thus, the noteworthy result of the present experiment is that even in post-guidance subsessions, the data fails to show that the progressive haptic guidance scheme is detrimental to performance.

Arguably, strong performance by the haptic guidance group early in training is to be expected since the guidance drives the participant along the desired trajectory at the desired excitation frequency. If participants rely solely on this guidance, their performance will be good but the guidance gains will decrease rapidly to the point that the magnitude of the guidance is not sufficient to drive the passive participant to complete the task. The participant must take control of the joystick and manipulate the virtual system to carry out the task. Toward the end of training, as the participants performance improves and the guidance diminishes, the participant's opportunity to rely on the guidance is eliminated. The post-guidance data fails to show significantly worse performance of the haptic guidance also indicating that the haptic guidance scheme used here may make it difficult for participants to rely on the existence of guidance as occurred with fixed gain guidance.

The CHAID decision tree also exposes significant differences between guidance modes within the sessions. The results show that from sessions 2 through 7, the haptic guidance mode is significantly different from visual guidance and practice alone. These data suggest that the proposed haptic guidance can be applied early in training without affecting the training outcome. Interestingly, the performance gains obtained by the haptic guidance are not obtained by visual guidance. These results suggest that haptic guidance, based on key skill measurements, is effective early in the training protocol when participants are beginning to understand the skills required for the task but should be progressively removed to avoid possible dependence. Finally, the resolution of the experiment design may have been too coarse to capture the changes in performance occurring in the first three sessions. An experiment with finer resolution may be required.

5 Conclusions

Novel haptic interface designs attempt to reproduce real-world tasks as accurately as possible or to provide virtual environment augmentation that will assist or guide the trainee in some way during skill acquisition. This paper presents the implementation of a progressive haptic guidance scheme designed to improve the efficiency of an augmented virtual training environment to be used for skill acquisition. The modification of a previously-developed virtual environment target-hitting task accommodates the guidance controller for investigation. The research compares the effectiveness of this scheme to a visual guidance that presents the same information in an exclusively visual way rather than using haptics. The research also compares these two schemes to practice alone (no guidance). The training protocol lasts eleven sessions over a two-month period. During each session, target hit count, trajectory error, and input frequency quantify performance. The latter two measures indicate the level of proficiency in the two key skills; by feeding these values into the controller, it updates the level of guidance offered to the participant. The analysis of the experimental results extend prior 1-session performance enhancement studies to a multi-session protocol. The analysis of the experimental results demonstrates that during the time the guidance is active, the haptic guidance significantly outperforms visual guidance and practice alone (no guidance) until late in the protocol when all three groups of participants saturate and converge at approximately the same level of performance. After each guidance subsession, all participants complete a short baseline test with no guidance. During these baseline subsessions the data failed to show significant differences between any of the groups. These data suggest that though the level of proficiency acquired during haptic guidance does not transfer to the unassisted condition at least it is not detrimental as previously reported. Our results confirm that haptic guidance based on skill component measures is effective early in the training protocol when participants are only beginning to understand the components of the task but should be progressively removed to avoid possible negative dependence on the guidance. These findings may be applied to an array of virtual environments used for surgical task training, vehicle control, sports training, physical therapy and rehabilitation.

Acknowledgements

This research was supported in part by a grant from the National Science Foundation (IIS-0448341). Huegel's residence at Rice was supported in part by the ITESM (Instituto Tecnolgico y de Estudios Superiores de Monterrey) in Guadalajara, Mexico. We thank Dr. Andrew Dick, Dr. Timothy Warburton, and Dr. Devika Subramanian all at Rice University for their assistance in recruiting participants for this study.

References

[1] J. J. Abbott and A. M. Okamura. Stable forbidden-region virtual fixtures for bilateral telemanipulation. *Journal of Dynamic Systems, Measurement, and Control*, 128(1):53–64, 2006.

[2] C. Basdogan, S. De, J. Kim, M. Muniyandi, H. Kim, and M. Srinivasan. Haptics in minimally invasive surgical simulation and training. In *Proc. IEEE Computer Graphics and Applications*, volume 24, pages 56–64, 2004.

[3] B. Bayart, A. Pocheville, and A. Kheddar. An adaptive haptic guidance software module for I-TOUCH: example through a handwriting teaching simulation and a 3D maze. In *IEEE International Workshop on Haptic Audio Visual Environments and their Applications*, pages 51–56, Ottowa, Canada, October 2005.

[4] B. S. Bell and S. W. J. Kozlowski. Adaptive Guidance: Enhancing Self-Regulation, Knowledge, and Performance in Technology-Based Training. *Personnel Psychology*, 55(2):267–306, 2002.

[5] N. Bernstein. *The Coordination and Regulation of Movements*. Pergamon, London, 1967.

[6] D. Chang. Haptics: gaming's new sensation. *Computer*, 35(8):84–86, 2002.

[7] J. Emken and D. Reinkensmeyer. Robot-enhanced motor learning: accelerating internal model formation during locomotion by transient dynamic amplification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(1):33–39, March 2005.

[8] D. Feygin, M. Keehner, and F. Tendick. Haptic guidance: experimental evaluation of a haptic training method for a perceptual motor skill. In *Proc. IEEE 10th Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (HAPTICS'02)*, pages 40–47, Orlando, FL, March 2002.

[9] R. B. Gillespie, M. O'Modhrain, P. Tang, D. Zaretzky, and C. Pham. The virtual teacher. In *Proc. of the ASME Dynamic Systems and Control Division*, pages 171–178, Anaheim, CA, Nov 1998.

[10] P. Griffiths and B. Gillespie. Shared control between human and machine: using a haptic steering wheel and aid in land vehicle guidance. In *Proc. IEEE 12th International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS '04)*, pages 358–366, Chicago, IL, March 2004.

[11] K. Henmi and T. Yoshikawa. Virtual lesson and its application to virtual calligraphy system. In *Proc. IEEE International Conference on Robotics and Automation, (ICRA 1998)*, pages 1275–1280, Leuven, Belgium, May 1998.

[12] F. C. Huang, R. B. Gillespie, and A. D. Kuo. Visual and haptic feedback contribute to tuning and online control during object manipulation. *Journal of Motor Behavior*, 39(3):179–193, May 2007.

[13] J. C. Huegel, O. Celik, A. Israr, and M. K. O'Malley. Expertise-Based Performance Measures in a Training Virtual Environment. *Presence: Teleoperators and Virtual Environments*, 18(6):TBD, 2009 (to appear).

[14] J. C. Huegel and M. K. O'Malley. Visual versus Haptic Progressive Guidance for Training in a Virtual Dynamic Task. In *Proc. IEEE Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '09)*, pages 399–400, Salt Lake City, UT, 2009b.

[15] Y. Li, J. C. Huegel, V. Patoglu, and M. K. O'Malley. Progressive shared control for training in virtual environments. In *Proc. IEEE Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '09)*, pages 332–337, Salt Lake City, UT, 2009b.

[16] Y. Li, V. Patoglu, and M. K. O'Malley. Negative efficacy of fixed gain error reducing shared control for training in virtual environments. *ACM Transactions on Applied Perception*, 6(1):21, January 2009.

[17] G. Lintern, S. N. Roscoe, and J. Sivier. Display principle, control dynamics, and environmental factors in pilot training and transfer. *Human Factors*, 32(3):299–317, 1990.

[18] M. K. O'Malley, A. Gupta, M. Gen, and Y. Li. Shared Control in Haptic Systems for Performance Enhancement and Training. *Journal of Dynamic Systems, Measurement, and Control*, 128:75–86, 2006.

[19] D. Reinkensmeyer, D. Aoyagi, J. Emken, J. Galvez, W. Ichinose, G. Kerdanyan, J. Nessler, S. Maneekobkunwong, B. Timoszyk, K. Vallance, et al. Robotic gait training: toward more natural movements and optimal training algorithms. In *Proceedings IEEE 26th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC 2004)*, volume 2, pages 4819–4821, San Francisco, CA, September 2004.

[20] D. Reinkensmeyer, J. Emken, and S. Cramer. Robotics, Motor Learning, and Neurologic Recovery. *Annual Review of Biomedical Engineering*, 6(1):497–525, 2004.

[21] L. B. Rosenberg. The use of virtual fixtures to enhance operator performance in time delayed teleoperation. *Journal of Dynamic Systems Control*, 49:29–36, 1993.

[22] G. Srimathveeravalli, V. Gourishankar, and T. Kesavadas. Comparative study: virtual fixtures and shared control for rehabilitation of fine motor skills. In *Proc. IEEE Second Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems (WHC '07)*, pages 304–309, Tsukuba, Japan, March 2007.

[23] G. Srimathveeravalli and K. Thenkurussi. Motor skill training assistance using haptic attributes. In *Proc. IEEE First Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, (WHC '05)*, pages 452–457, March 2005.

[24] L. M. Sutherland, P. F. Middleton, A. Anthony, J. Hamdorf, P. Cregan, D. Scott, and G. J. Maddern. Surgical simulation: a systematic review. *Annals of Surgery*, 243(3):291–300, March 2006.

[25] 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. In *Proc. IEEE 5th International Workshop on Robot and Human Communication, 1996*, pages 32–37, Tsukuba, Japan, Nov 1996.