Motor Skill Acquisition in a Virtual Gaming Environment

Nicole Howie*, Sagar N. Purkayastha†, Michael D. Byrne*, Marcia K. O'Malley†
*Department of Psychology, †Department of Mechanical Engineering and Materials Science, Rice University

There are many domains that still require use of complex manual control, despite the general shift in the field toward research on supervisory control. One of the problems in complex manual control is training; we currently lack models that can help guide training. The research reported here is part of an effort to fill that gap. In this study, we used the Neverball video game as a motor control task and used performance metrics from the game to measure learning. In addition, we collected motion data to determine what basic movements correlated with game performance. Subjects showed evidence of learning in almost all of the performance metrics, which will enable comparisons with the motion data. The ultimate goal is to use the motion data to identify basic movements that underlie successful performance to provide as feedback during training, and hopefully accelerate learning.

INTRODUCTION

There are many domains that still require manual control, such as medicine (remote surgery and stroke rehabilitation), gaming, and the military (unmanned vehicles, and virtual reality training environments). However, due to automation, research on human performance and the use of dynamic, multiple-degree-of-freedom manual control has decreased substantially over the last two decades. Research instead has instead been increasingly focused on supervisory control rather than direct manual control. Nonetheless, manual control is still a crucial problem in numerous domains. Better understanding of how human motor skills are acquired would allow us insight into how to train people for these domains, where we presently rely almost exclusively on the expertise of subject matter experts. Training is still often conducted essentially via apprenticeship. A deeper understanding of motor skill acquisition could lead to the ability to accelerate training and predict how long it takes to turn a novice to an expert. Another application would be aiding the rehabilitation of those who have lost motor skills due to stroke or traumatic brain injury.

The human factors literature has no shortage of control system models of manual control and tracking, such as the optimal control theory and crossover model (Jagacinski & Flach, 2003). While these models have been useful for many tasks in the past, they are generally focussed on performance, not skill acquisition. Therefore, it is unclear how these models would be applicable to our interest of learning how people acquire motor skills.

Our starting point for this research was the target-hitting task used by O'Malley and colleagues (O'Malley, et al., 2006; Li, Patoglu, & O'Malley, 2009; Huegel, et al., 2009). The target-hitting task is a haptic-enabled virtual task, which is used for motor skill training. In the task an operator uses a joystick to control a disk on a computer screen. The disk is coupled to a second disk. The goal of the task is to move the disk controlled by the operator, such that the coupled disk hits both targets on the screen in succession. As shown in Figure 1, the disks are modeled as masses coupled by a damped spring.

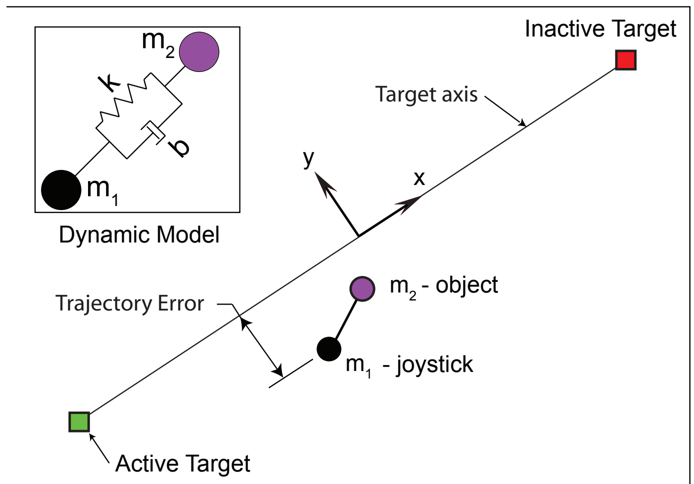


Figure 1. Target-hitting task. m1 is controlled by an operator using a joystick. The objective is to alternate hitting two targets with m2 (termed the "disk").

In a study conducted by Huegel (2009), participants were classified into three types of learners: high performers, low performers or transitional performers. High performers were defined as being one standard deviation above the mean in initial performance. These performers started out strong, made modest improvements and generated high scores across all trials. Low performers were defined as subjects whose final hit count performance was more than one standard deviation below the mean in initial performance. The low performers improved only slightly across experimental sessions. Transitional performers had characteristics of both groups; they started out performing poorly like the low performers, but performed as well as high performers in the end as depicted in Figure 2.

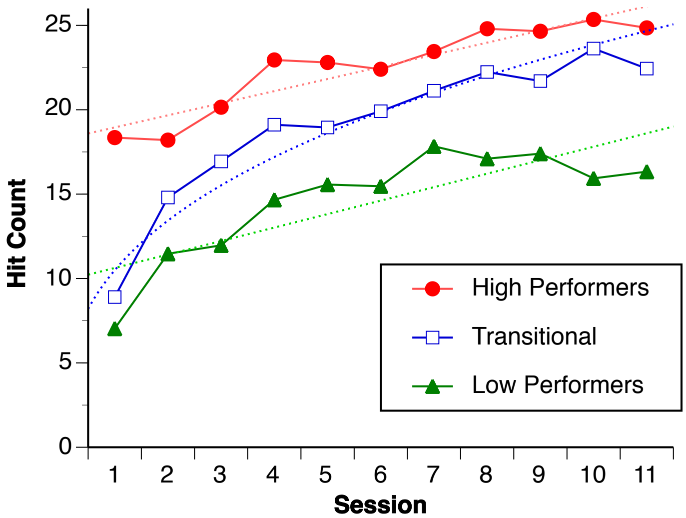


Figure 2. Mean hit count per trial across sessions for the classification of learners in target-hitting task.

Huegel (2009) examined movement characteristics of subjects who performed well on the task. Movements for these subjects were characterized by having low off-axis error, meaning that they moved on a straight path, back and forth along the target axis, whereas other subjects tended to move in circles. In addition, better performers of this task were able to oscillate with the natural frequency of the system, while other subjects tended to try to move as rapidly as possible. In short, these results provide interesting insight into how motor skills are learned. However, what the original research did not reveal is whether the results extend to other motor skill tasks; this study attempts to answer this question.

Unfortunately, the target-hitting task is not without shortcomings. One is the costly haptic-enabled joystick needed to perform the task. The second is the repetitive nature of the task; participants grew bored quickly. Because of these concerns, we conducted a preliminary study using the Neverball video game as the motor skill task and employed three controllers to be used as joysticks. The main purpose of the study was to determine if there were any systematic differences between video game controllers, so we could get an accurate measure of learning. We used performance metrics from the game, such as completion time, level termination reason and the number of coins collected as measurement of learning. In addition, raw motion data was captured, which was intended to allow us to identify strategies used by subjects to play the game. Overall, the preliminary study provided us with four main results:

- Game levels presented did vary substantially in difficulty.
- We found no evidence of differences between controllers, which suggested that if learning occurred, it was independent of the controller used.
- No evidence of learning across sessions. This may have been a result of switching between controllers.
- The motion data we collected was ambiguous. Game controllers use accelerometers to detect motion. However, because the controller is operated in the earth's gravity field, acceleration in, for instance, the left-right axis is registered both when the controller is moved left or right, or when it is tilted left or right. Thus, raw accelerometer data cannot distinguish between translational and rotational movements, making it difficult to identify movement strategies associated with higher performance.

Using the preliminary results as a guide, we conducted the present study to determine if learning is present in the Neverball environment. This was achieved by addressing issues encountered in the preliminary study. Specifically, we reduced the number of controllers used to play the game from 3 to 1, which diminished interference from a change in controllers. Also, we provided more time for subjects to play each level to increase learning. In addition, we used a video camera to record each subject's hand as they played the game to differentiate rotational from translational movement and identify strategies. Our hope was that this study would bring us one step closer to determining if the results from the target-hitting task extend to the Neverball video game.

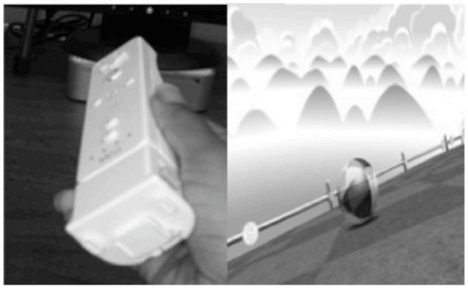
METHOD

Subjects

Fifteen undergraduate and two graduate students from Rice University participated in this study. The subjects consisted of 9 females and 8 males, aged between 18 and 27. Subjects were recruited from flyers posted around campus and received $25 for compensation. In addition, subjects were eligible for a bonus gift card if their final score was the highest.

Stimuli and Materials

The Neverball video game was used for this study. In this game a ball is controlled by gravity using a controller to tilt the playing field of level as shown in Figure 3. Tilting the playing field can be used to steer the ball to coins and away from obstacles. Coins are collected when they are hit by the ball. Coins come in three different colors, which have the following values: Yellow is 1, Red is 5, and Blue is 10. Each level has a minimum number of coins necessary to unlock the goal in a time limit. In order to complete a level the ball must enter the unlocked goal. In this study, the game was played in normal fashion; however, subjects were encouraged to collect the most amounts of coins in the least amount of time.



a. b.

Figure 3. The Nintendo Wii remote with a MotionPlus attachment (a) is being used to tilt the playing field (b) to the left in the Neverball video game.

Five levels of the Neverball game were presented to subjects in order of increasing difficulty. Each level had different obstacles, which required distinct movements that the subject had to employ to navigate the ball around the playing field to complete the level. In levels 1 and 2, there was a rail to keep the ball on the playing field. However, both levels required a combination of controlled speed and fine motor movements to successfully complete the levels. Levels 3 and 4 had no rails. These levels required the subject to make slow and precise motor movements to steer the ball around turns to prevent falling out of the level. Lastly, level 5 had characteristics from levels with and without rails. Of the 5 levels, this level was effectively impossible to beat and was designed to mirror the target-hitting task. Like in the target-hitting task, subjects used a controller to alternate hitting two targets, which appear on the screen in succession. However, in this level the targets are coins and are located on the sides of the playing field, which is shaped like a bowl. In order to collect coins, subjects had to use fast movements to traverse the playing field.

The Neverball video game was played on a 15 inch LCD screen set to a resolution of 1024 by 768 pixels. The computer used was a 1.83 GHz Macintosh Mini running the Windows XP operating system. A Cirago Bluetooth dongle was used to connect the Nintendo Wii remote with a MotionPlus attachment (MotionPlus remote) to the computer. "The MotionPlus uses multiaxis gyroscopes to sense rotational movement" (Shah, 2009, para. 2). This attachment in combination with the standard Wii remote allows movements to be detected and captured with greater accuracy. In order to use the MotionPlus remote as a regular joystick on a Windows operating system, two bridging technologies were required. The first step involved using the GlovePIE program, which allows input from controllers to emulate input devices, such as a keyboard or mouse. In this case, the MotionPlus remote emulated a joystick; accelerometer values were translated to joystick positions. Second, we used a program called PPJoy, which is a virtual joystick driver that allows for the virtual joystick created by GlovePIE to be recognized as a joystick on Windows. Also, during game play GlovePIE recorded movement data transmitted by the MotionPlus remote. This motion data consisted of accelerometer values sampled at a rate of 40Hz. More information about GlovePIE and PPJoy can be found at: http://glovepie.org/glovepie.php and http://ppjoy.bossstation.dnsalias.org, respectively.

Design

Each subject completed 3 one-hour sessions. During each session, 5 levels of the Neverball game were played using the MotionPlus remote controller. During game play, dependent measures collected included raw motion data, video of the subject's hand performing the task, and performance metrics from each level. We recorded the subject's hand with a video camera while they completed the task. The video allowed us to identify different strategies the subject used to play the levels. The performance metrics recorded for each level were completion time, number of coins collected and reason for the end of level. The reasons a level could end were if the subject: completed the level successfully (successes), fell out of the level (fall outs), or ran out of time (time outs).

Procedure

In each session participants were seated in front of a computer and read instructions on how to play the Neverball video game and use the MotionPlus remote. Additionally, subjects were given instruction to record the session, level, and number of attempts on a dry erase board in view of the video camera used to record their hands. After presentation of the instructions, the experimenter answered any questions that arose. At this point, a video camera was started to record the session. Subjects played each level for 10 minutes: a timer was used to keep track of the time. After this time was up and the level currently played was over, the experimenter guided subjects to the next level. While subjects played the game, the experimenter recorded performance metrics and used a keyboard to direct the computer to start and stop motion data collection. After playing the game on the third session, subjects filled out a survey and were debriefed.

RESULTS

A repeated measures ANOVA (with Greenhouse-Geisser correction where appropriate) was performed on the Neverball performance metrics: coins, fall outs, time outs and successes. Data from the first trial of level 3 for every session was excluded due to problems with the recording of the data. Each metric was analyzed with session and level as the independent variable. Due to levels being presented in order of increased difficulty, there was an effect of level for every metric.

Additionally, for the performance metrics that showed an effect of session, a further analysis was conducted to examine whether there was a difference between levels with and without rails. The levels with rails were levels 1 and 2. The levels without rails were 3 and 4. Level 5 was excluded from this analysis because it had characteristics of both types.

Number of Coins Collected

The average number of coins collected for each level by session is displayed in Figure 4. For levels 1 through 4 the amount of coins collected increased with each session. The main effect of session was reliable, $F(2, 20) = 19.42, p < .01$, MSE = 75.44. Posthoc tests showed that the means for all three sessions were significantly different. In addition, there was an interaction of session and level, $F(3.22, 32.23) = 2.98$, p = .043, MSE = 139.87.

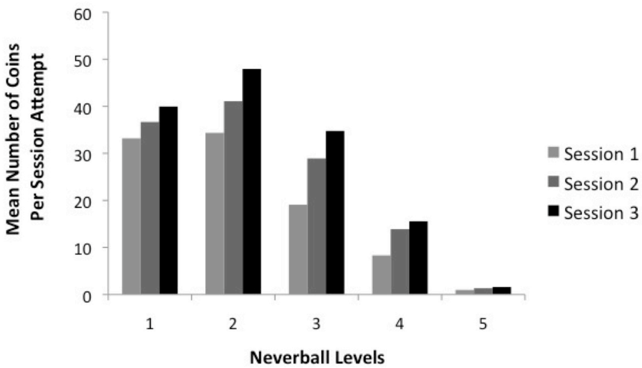


Figure 4. The mean number of coins collected for levels played in the Neverball video game for three sessions.

The mean number of coins collected for each session for levels with and without rails are displayed in Figure 5. This figure shows that subjects improved across sessions for both types of levels. However, they collected less coins for levels with no rails. The main effects of session $F(2, 32) = 20.19, p < .01$, MSE = 199.36 and rails $F(1, 16) = 150.68$ $p < .01$, MSE = 238.60 were both reliable.

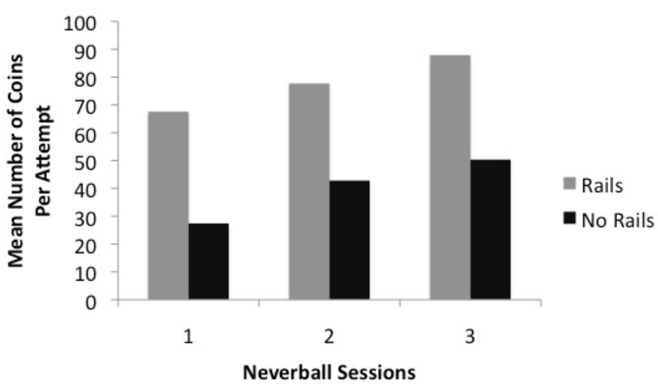


Figure 5. The mean number of coins collected across session for levels played with and without rails in the Neverball video game.

Number of Fall Outs

For this metric, smaller numbers indicate better performance. The overall number of fall outs across sessions was 56.49 (SD = 14.17). The mean number of fall outs for each session were 55.24, 56.06, and 58.18. This effect was not significant, $F(1.26, 12.64) = .98, p = .37$, MSE = 30.71.

Number of Successes

The mean number of successes per session on each level are shown in Figure 6. As expected, level 5 had no successes. Also, level 4 showed less improvement, most likely because it was difficult to complete. The main effect of session was reliable, $F(2, 20) = 7.034, p = .01$, MSE = 2.54. In addition, there was an interaction of session and level, $F(4.19, 41.91) = 3.01, p = .023$, MSE = 2.18.

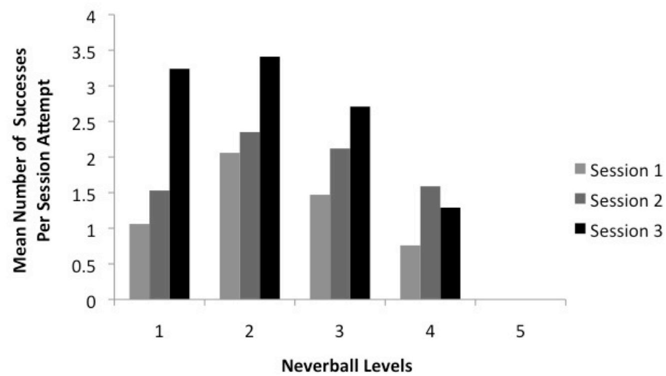


Figure 6. The mean number of successes for levels played in the Neverball video game for three sessions.

The average number of successes for each session for levels with and without rails are shown in Figure 7. This figure shows that both groups improved across sessions. However, subjects had more successes with levels that had no rails. The main effect of session $F(2, 32) = 11.29, p < .01$, MSE = 5.32 and rails $F(1, 16) = 4.78$. $p = .044$, MSE = 8.14 were both reliable.

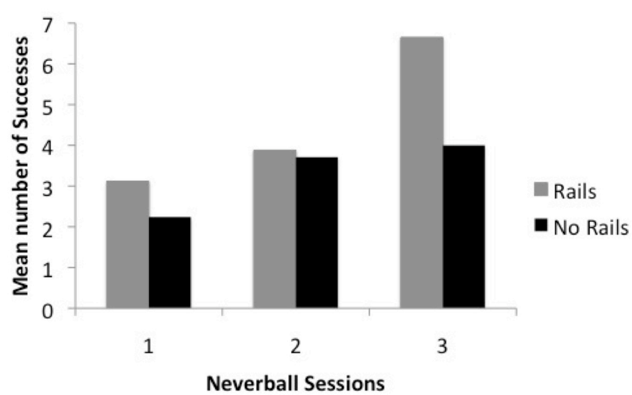


Figure 7. The mean number of successes across session for levels played with and without rails in the Neverball video game.

Number of Time Outs

For this metric, smaller numbers indicate better performance. The mean number of time outs for each session were 17.35, 15.41, and 13.88. The main effect of session was reliable, $F(2, 20) = 6.02$, $p = .01$, MSE = 1.53. Post hoc tests revealed that there was a difference in the number of time outs for session 1 and 3, but not for session 2 and 3.

The mean number of time outs vs. rails for each session is shown in Figure 8, which shows that across sessions subjects incurred more time outs for levels without rails. The main effect of session and rail were significant, $F(2, 32) = 10.12$, $p < .01$, MSE = 2.56 and $F(1, 16) = 115.13$, $p < .01$, MSE = 6.58.

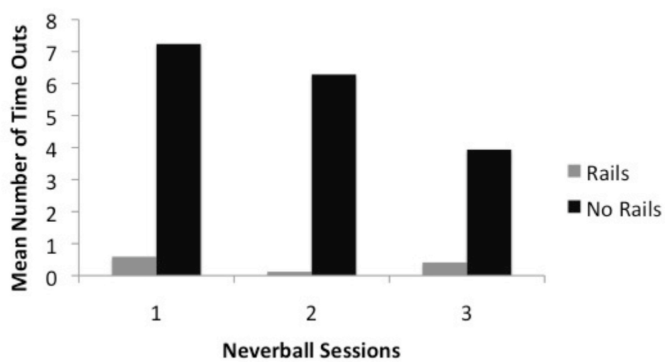


Figure 8. The mean number of time outs across sessions for levels played with and without rails in the Neverball video game.

DISCUSSION

Our primary concern in this domain is whether subjects would show meaningful improvements in performance over the relatively short performance interval. Fortunately, overall the results from the performance metrics were encouraging; we were able to provide evidence of learning and identify experts in Neverball. Subjects showed improvement on almost all of the performance metrics used from the Neverball video game. There were two exceptions. First, subjects did not improve on fall outs per session. However, this is one of the less critical measures. The second exception concerns one of the specific Neverball levels, on which subjects performed poorly across all sessions.

It remains an open question whether or not subjects can be classified into the three types of learners mentioned in the introduction; these data do not show evidence of such a split. Our goal was to determine if this classification of learners found for the target-hitting motor task was generalizable to the Neverball motor task. This will likely require more training sessions and possibly tasks of somewhat higher difficulty, though clearly not as difficult as our Neverball level 5.

Ultimately we would like to use these data to inform training of motor skills. One of the challenges in training motor skills is that it is difficult to provide feedback to trainees without knowing what the fundamental movements are that they should be executing. With performance data indicating learning and a detailed source of motion data, we should be in position to examine the relationship between underlying movements and performance measures.

Based on the performance data reported here, we have been able to identify expert subjects on the basis of combining coins collected and time to success. The next step is to examine the motion data to determine if performance on specific levels can be correlated with properties of those data. Of course, there is a considerable volume of accelerometer data, not unlike eye-tracking data. However, unlike with eye-tracking data, methods of analysis for such data are not well-developed and it is not yet clear how best to analyze the raw accelerometer data.

However, we have made some progress on this score. For example, a preliminary analysis suggests that for Level 2, average movement frequency on the left-right axis correlates somewhat negatively with the number of coins collected, and the derivative of acceleration on that axis (that is, the movement "jerk") is positively correlated with the number of coins collected. Our plan is to continue to examine various measures derived from the motion data with the hope of discovering what the fundamental movements are that subjects need to execute in order to produce good performance.

ACKNOWLEDGEMENTS

This research was supported by the National Science Foundation under grant #IIS-0812569. The views and conclusions contained herein are those of the authors and should not be interpreted as representing the official policies or endorsements, either expressed or implied, of the NSF, the U.S. Government, or any other organization.

REFERENCES

Huegel, J. C. (2009). Progressive Haptic Guidance for a Dynamic Task in a Virtual Training Environment. Doctoral Dissertation, Rice University, Houston, TX.

Huegel, J. C., Celik, O., Israr, A., & O'Malley, M. K. (2009). Expertise-based performance measures in a virtual training environment. *Presence: Teleoperators and Virtual Environments, 18*(6), 449–467.

Jagacinski, R. J., & Flach, J. M. (2003). *Control theory for humans: Quantitative approaches to modeling performance*. Mahwah, NJ: Erlbaum.

Li, Y., Huegel, J. C., Patoglu, V., & O'Malley, M. K. (2009). Progressive shared control for training in virtual environments. In *Proceedings of the International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems and the Third Joint World Haptics Conference (HAPTICS)* (pp. 332–339).

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

O'Malley, M. K., Gupta, A., Gen, M., & Li, Y. (2006). Shared control in haptic systems for performance enhancement and training. *ASME Journal of Dynamic Systems, Measurement and Control, 128*, 75–85.

Shah, Sarju (2009). *Wii Motion Plus Hands-on Update*. [Review of the video game remote controller *Wii MotionPlus*, produced by Nintendo, 2009]. (n.d.). Retrieved from http://www.gamespot.com/features/6194443/index.html