MOTOR LEARNING IN HUMANS IN RESPONSE TO AN ADAPTIVE GAMING ENVIRONMENT

by

SYDNEY BRIGHT

A THESIS

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Michael Hahn, PhD

Motor control rehabilitation techniques are crucial for the recovery process of amputees or patients suffering from motor control pathologies such as a stroke. Developments in motor learning techniques can vastly aid in the efficiency and comfort of treatment, which is important for patients who have already suffered so much. To expand upon current research, a video game with a controller that uses EMG technology was designed to test the efficacy of using computer learning technology to aid in motor learning. Motor learning outcomes were recorded between three cohort groups that played three different versions of the same game. A sample of able-bodied subjects were assigned to three different experimental groups. One group played with an adaptive Artificial Intelligence (AI) structure programmed within the game that made the game relatively easier as time went on, another version of the game was made to have random difficulties every round, and the last group had the game difficulty increase over time. The motor learning outcomes (demonstrated in a 24-hour retention test) of these three groups were compared, to judge which environments were best for motor learning. Overall, group differences were statistically insignificant, yet they suggest a general trend that motor learning for the AI group was lowest, as predicted.

Additional analysis of subject sub-groups, and the quality of AI code is also explored. This type of research can help medical practitioners get a better idea of what methods are best suited for motor rehabilitation.

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Introduction

Skeletal muscle activation can be identified by the voltage differentiation propagated down the sarcolemma once a motor neuron sends a signal to contract. Every time a neuron is activated, charged potassium ions leave the cell, and charged sodium ions enter the cell. This exchange of charged ions generates a positive voltage potential across the membrane that propagates all the way down the motor neuron pathway from the brain to the skeletal muscles. Therefore, every time a muscle is contracted, a voltage change pattern can be detected at the surface of the muscle. If one were to place recording electrodes on the contracting muscle, one could use computer devices to detect and react to the voltage changes during muscle activation. This also allows for the ability to convert neuronal signals into computer signals, turning the human body into a controller, capable of generating computer code commands.

This type of technology has allowed researchers to examine the rehabilitation of arm muscles, with patients training via body-controlled video games (Donoso Brown, Dudgeon, Gutman, Moritz, & McCoy, 2015; Donoso Brown et al., 2014; Moritz et al., 2011; Rios et al., 2013). To test theories related to this field, video games that respond to specific neuronal commands can be used to observe trends in Artificial Intelligence (AI) capabilities, motor learning patterns, etc.

This type of research and technology has paved the way for the creation of robotic hands or limbs that can be commanded and controlled through neurons either in the limb itself or the brain. With that, it will be important that robotic prostheses not only be controllable through neuronal activation, but that the robotic limb will learn the specific neuronal anatomy and patterns of the user, so that the arm can be controlled like it was the natural organic hand of the owner.

Literature Review/Background

Human motor learning especially in the forearms, has been the focus of a substantial amount of research. Motor retention is best tested after 24 hours due to the consolidation of motor memories over that time period (Brashers-Krug, Shadmehr, & Bizzi, 1996). It has been observed that active learning rather than passive learning has a significant effect on motor learning in the forearm muscles (Martinez & Otero, 2014). Furthermore, motor learning outcomes are better when the test is given at random levels of difficulty compared to a difficulty that changes in a linear fashion (Hinkel-Lipsker, 2017).

Many studies have observed the effectiveness of motor learning and rehabilitation using video games. Studies involving electroencephalography (EEG) have demonstrated that brain-computer interface (BCI) technology has a positive effect on motor rehabilitation (Pichiorri et al., 2017). Many studies have involved take-home video games called NeuroGame Therapy (NGT) where subjects are asked to routinely play using the muscles of the arm needing rehabilitation (Donoso Brown, Dudgeon, Gutman, Moritz, & McCoy, 2015; Donoso Brown et al., 2014; Moritz et al., 2011; Rios et al., 2013). All these studies have involved Surface Electromyography (sEMG) to detect muscle activity, and in some form transferred these data to a computer to elicit a command in a video game. The results from these studies support the use of video game play as an effective motor learning rehabilitation technique. However, determining effective routines and schedules for patients has proven to be difficult (Donoso Brown et al., 2015, 2014). These types of treatments can be muscle-specific, and entertaining which can be useful for both children and adults. (Moritz et al., 2011; Rios et al., 2013). In the end, many studies recognize the need for further investigation, to see if targeted use of these muscles can actually be used as treatment for motor control rehabilitation.

There has also been much research in developing gaming AI technology, especially in industry. However, little is known about the effect of an AI system that adapts to player outcomes, to specifically tailor the game for ease of use, and how this may affect motor learning outcomes. There have been studies that use neural network robots controlled by EMG signals but these have been focused on how the computer can better discriminate between noise and the action potential signal from the arm (Fukuda, Tsuji, Ohtsuka, & Kaneko, n.d.).

The overall objective of this study was to observe the extent of motor learning that can occur in a sample of healthy human volunteers interacting with an AI that learns and adapts to each player to make the game as easy as possible. Therefore, the purpose of this study was to determine how an adaptive gaming environment affects motor learning outcomes. It was hypothesized that AI-controlled training will show the least motor learning, and that random difficulty training will produce the most motor learning.

Methods

Research Population & Recruitment Methods

Forty-eight research subjects (19 female, 29 male) were recruited from the University of Oregon community. The age criteria for the experiment was anywhere between the age of 18-65. Exclusion criteria for participants were confined to extremely poor vision, or an inability to use recruit forearm muscles, which would make the game completely unplayable.

Experimental Setup

In this experiment, a Myoband (Myo™. Cambridge, MA)) sensor array wasplaced around the upper forearm. The Myoband contains electrodes that record the voltage output from muscle activation and sends a signal to a computer via Bluetooth. The Myoband sensor array was used as a trigger controller for a computer game that uses the muscle activation signal to cause a character in the video game to “jump”. The video game is a distance-survival based game where the player must keep the character (a bird) off the ground while it passes through several non-lethal obstacles. Participants were asked to not only travel as far as they could, but as accurately as possible to follow some lines or stay within pipes for tests of accuracy (Figures 1 and 2).

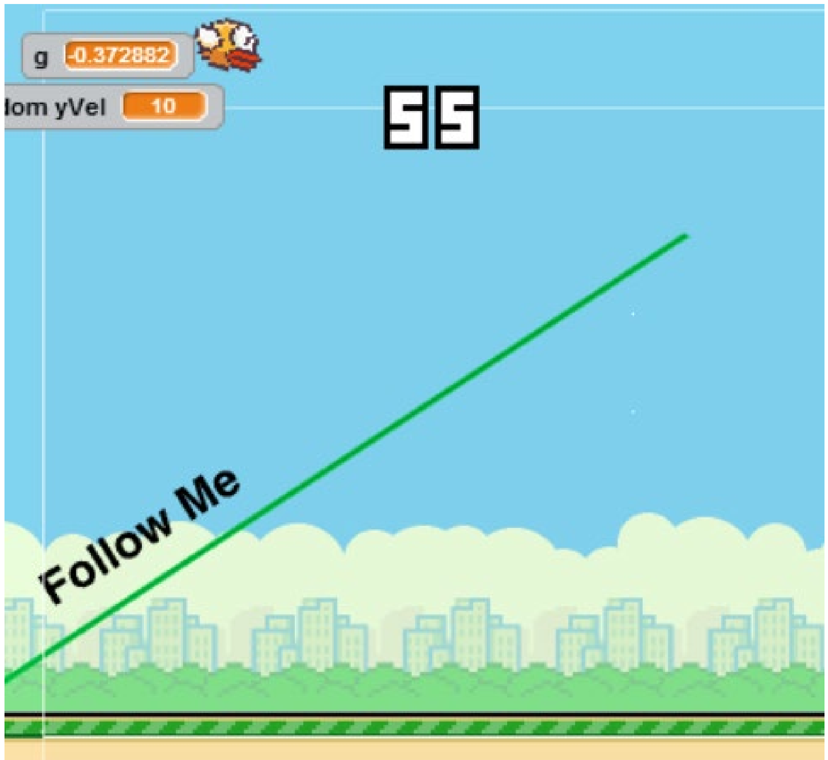


Figure 1: Image of the first half of pyramidal line test in the game.

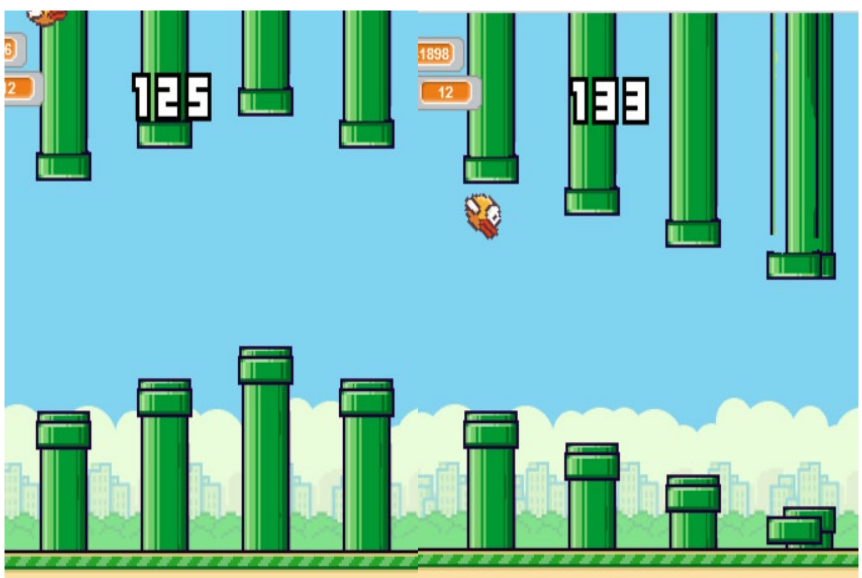


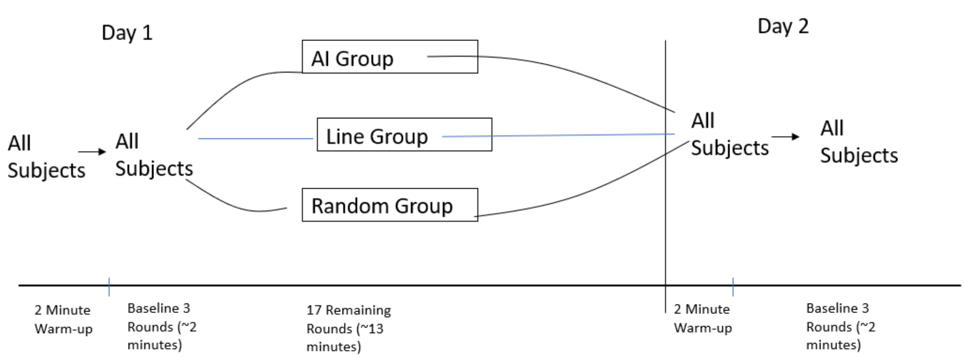
Figure 2: Image of the pipe test in the game.

Procedure

On Day 1, each subject played 2 minutes of the game with no scores recorded. The purpose of this trial was to familiarize subjects with the hand gestures that were needed to play the game. The first 2 minutes were set to an easy level of difficulty so that the player could become familiar with the controls without difficulty. The next three games were designed to set an initial skill level that the AI used as a reference to adapt to the individual performance level of each player. These three games were also recorded as baseline scores to be compared against scores from a test set of games on Day 2.

All subjects were separated into three groups at random: an AI learning group, a randomized difficulty group, and a progressively harder difficulty group. Each setting provides a different environment where the player learns to play the game differently given the variable amount of difficulty they are presented with each round (20 total rounds). For example, the AI learning group will experience game difficulty tailored to their specific performance, and therefore experience the game getting easier. Whereas the progressively harder difficulty group's difficulty setting will simply increase linearly within the confines of the settings used in the three baseline rounds' difficulty. The subjects then played about 15 more rounds of the game (the 'learning' phase). Various scores were recorded from the game during the learning phase. Throughout one round of the game, overall distance was scored, and accuracy scores were calculated based upon how well the player maneuvered through the obstacle course.

Subjects were asked to come in 24 hours later. They were given an initial two minutes like the previous day to warmup after a night of not playing. Then they played three rounds of the game with the same difficulty settings that all players were given in the Baseline stage of Day 1. Scores from these three rounds were compared to those from the Baseline session on Day 1.



Statistical Analysis

Upon completion of the two-day protocol, an average overall score was recorded for each subject from the distance travelled, and recorded scores for the trajectory accuracy across both sets of test rounds at the beginning of Day 1 and the end of Day 2. The overall distance score changes from Day 1 to Day 2 were compared across all subject groups and two tailed t-tests were used to test for statistical significance (alpha = 0.05).

Given the observed variance within the data, sub-group analysis of the data was performed to further interpret the data. For this analysis, the participants were separated into three groups: a ‘Gamer Group’ of subjects who demonstrated preexisting skill in playing the game on Day 1 (criteria: of the first three rounds, making it to the third line test in the first game, or making it to the second line test in the second game, or making it to the first line test in the third game) (n=15); a 'non-responsive' group of subjects who scored a score higher than 0 only once on the first day, and only twice on the second day on any obstacle (n=8); and a 'Middle' group of subjects who fall under neither category, and can be seen as a more typical or expected subject (n=25). Similar analysis of the overall distance score was used for each group to examine any relationships.

Finally, the score of each progressive round for all 'AI' subjects was analyzed briefly to suggest the strengths or weaknesses of the AI code used.

Results

Main Analysis

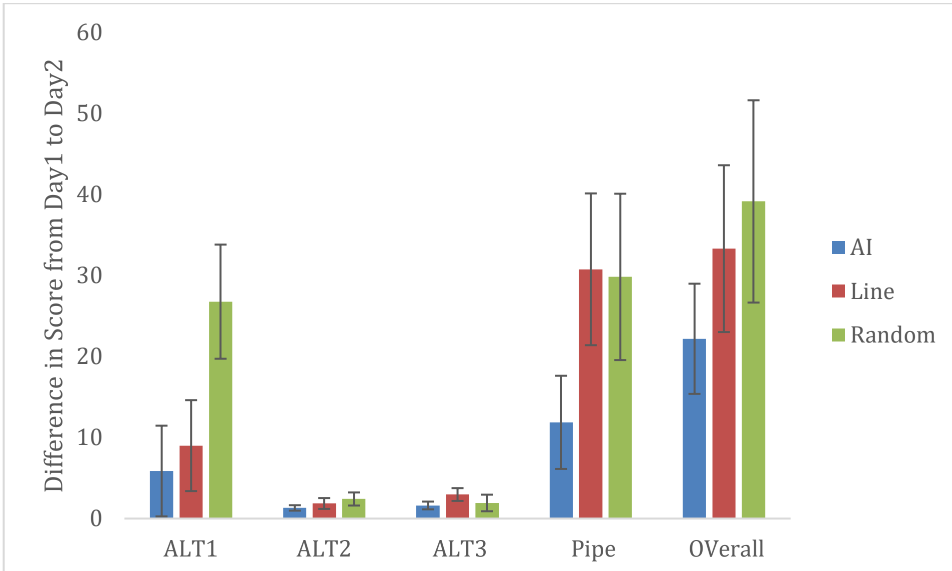


Figure 3: Score difference between Day 1 and Day 2 across all cohort groups for all 5 scores: the first horizontal line test (ALT1), the first pyramidal line test (ALT2), the second pyramidal line test (ALT3), the pipe test score, and overall distance travelled score.

Table 1: Summary of all the differences between day 1 and day 2 game scores across all cohorts (Total N=48, AI n=16*, Line n=16*, Random n=16), data are presented as points ± standard error									
	ALT1			ALT2			ALT3		
	AI	Line	Random	AI	Line	Random	AI	Line	Random
Average Score	5.87 ± 5.60	9.00 ± 5.61	26.77 ± 7.05	1.31 ± 0.34	1.86 ± 0.67	2.42 ± 0.81	1.62 ± 0.48	2.97± 0.79	1.92± 1.02
	Pipe Score			Overall Distance Score					
	AI	Line	Random	AI	Line	Random			
Average Score	11.88 ± 5.75	30.77 ± 9.37	29.83 ± 10.27	22.19 ± 6.80	33.32 ± 10.30	39.15 ± 12.49			

*Note : Due to data corruption, subject #45's (AI group) ALT2 score was not incorporated into the data above. Same with subject #31 (Line Group) who had corrupted data involving ALT1 and ALT2.

Table 2: T-test results from overall distance score between the three cohort groups: all subjects ($\alpha = 0.05$)			
	AI vs Line	Ai vs Random	Line vs random
P value	0.19	0.12	0.36

Sub-Group Analysis from Data Above

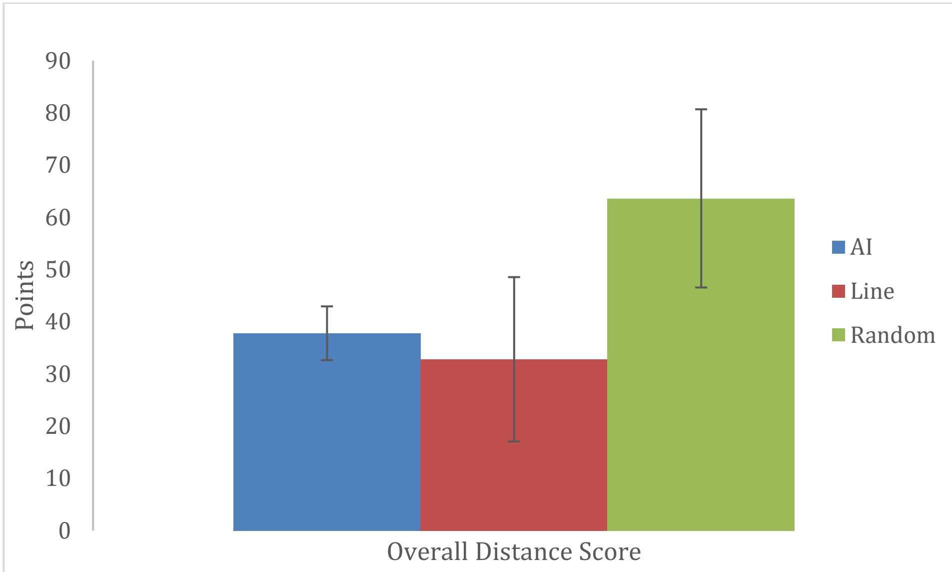


Figure 4: Difference of overall distance scores across day 1 and day 2 for all three cohorts, only for the 'middle' skill subjects (n=25)

Table 3: Summary of differences between day 1 and day 2 game scores for the 'middle' skill subjects (n=25)			
	Overall Distance Score		
	AI	**Line**	**Random**
Average	37.80 ± 5.15	32.82 ± 15.74	63.63 ± 17.06

Table 4: T-test results from overall distance score between the three cohort groups for the 'middle' skill subjects (α = 0.05) (n=25)			
	AI vs Line	Ai vs Random	Line Vs random
P value	0.38	0.048	0.10

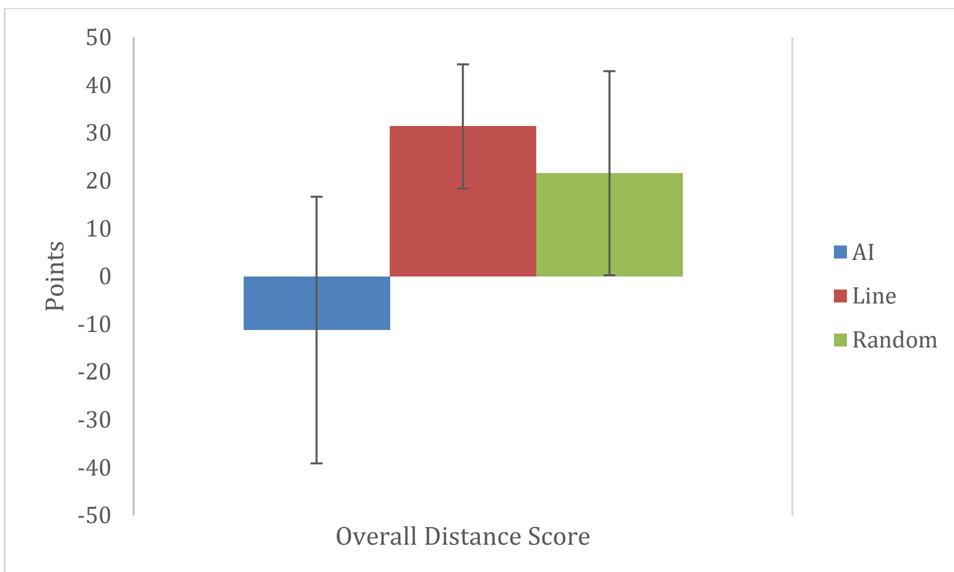


Figure 5: Difference of overall distance scores across day 1 and day 2 for all three cohorts, only for the 'gamer' subjects (n=15)

Table 5: Summary of differences between day 1 and day 2 game scores for the 'gamer' subjects (n=15)			
	Overall Distance Score		
	AI	**Line**	**Random**
Average	-11.22 ± 27.88	31.37 ± 12.99	21.60 ± 21.34

Table 6: T-test results from overall distance score between the three cohort groups when looking at the 'gamer' subjects (α = 0.05) (n=15)			
	AI vs Line	Ai vs Random	Line Vs random
P value	0.083	0.24	0.36

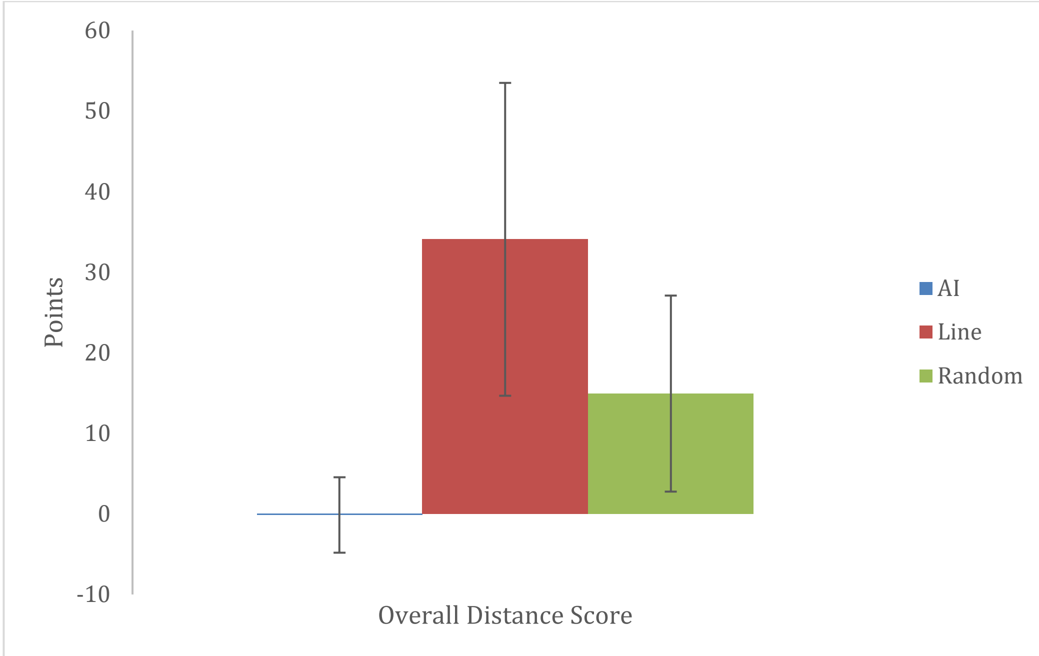


Figure 6: Difference of overall distance scores across day 1 and day 2 for all three cohorts, only for the 'non-responders' subjects (n=8)

Table 7: Summary of all the differences between day 1 and day 2 game scores for the 'non-responder' subjects (n=8)

	Overall Distance Score		
	AI	**Line**	**Random**
Average	-0.13 ± 4.68	34.08 ± 19.42	14.93±12.17

Table 8: T-test results from overall distance score between the three cohort groups for the 'non-responder' subjects (α = 0.05) (n=8)

	AI vs Line	Ai vs Random	Line Vs random
P value	0.034	0.11	0.25

AI code Analysis

Table 9: A count of how many subjects reached the end of the course (the pipes), and the average number of times the subject would reach the end within the 20 rounds of the game (Day 1).		
	Number of people who reached pipe test	Average amount of reaching the pipes
AI	16	4
Line	6	2.166
Random	11	2.545

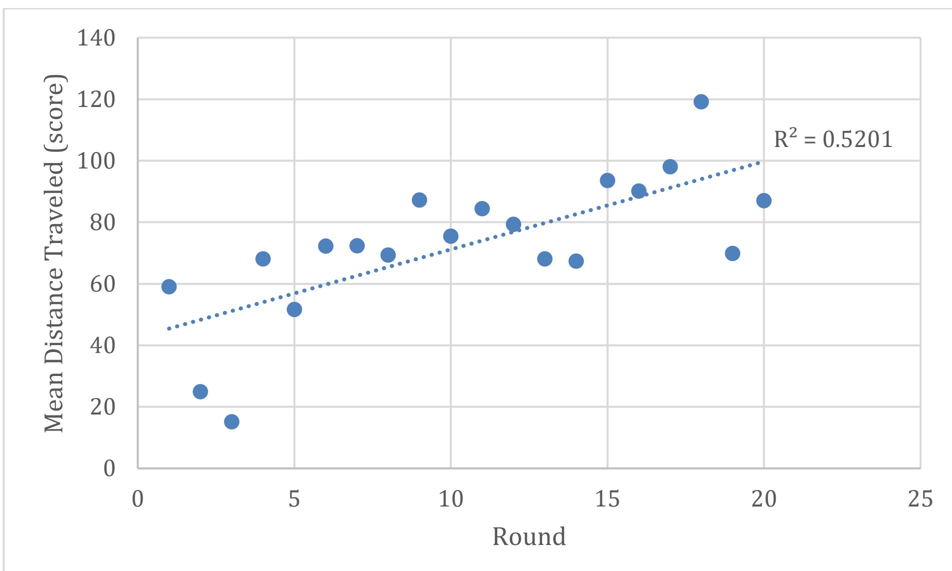


Figure 7: Mean scores of distances travelled for all AI subjects across the 20 games on day 1.

Discussion

The purpose of this study was to observe motor learning outcomes across three different groups while playing a video game controlled by EMG. It was hypothesized that the group with the AI embedded within the game would show the least amount of motor learning due to the fact that the AI attempted to make the game easier during the training day (Day 1). It was also hypothesized that the group with random difficulty settings would demonstrate the most motor learning, due to the inherently more difficult training experience. The game was made to have four different obstacle tests for accuracy, and one overall distance score, all for the purpose of analyzing the motor learning outcomes. However, most of the data for the obstacle tests were too variable to show statistical differences. For example: the average improvement score for the first obstacle within the AI group was 5.86 ± 5.59 points, the linear group for the same obstacle had an average score improvement of 9.00 points with a standard error of 5.61 points.

When it comes to the overall distance scores across Day 1 and Day 2, the AI group improved their distance travelled score by 22.19 ± 6.8 points, the linear group showed an average improvement of 33.32 ± 10.30 points, and the random group scored an average of 39.15 ± 12.49 more points. There are observable mean values that resemble the hypothesis with the AI group improving the least, and the random group improving the most. However, the variation is too high for the differences to be statistically significant. Therefore, no strong conclusion can be drawn.

Subgroups were created from the sample in an attempt to understand the source of the variation observed in the primary analysis. Upon further examination, it appears that there were three different types of subjects: those that were accustomed to the process of video games and were proficient at quickly learning controller techniques that are needed to succeed in a game (n=15), a group of people that have extreme difficulties understanding how to use the controller and were therefore unable to benefit from the program (n=8), and everyone else who fell in between (n=25).

With this division in mind, the overall distance scores were analyzed once more. For the 'middle' subgroup, the mean improvement of the AI group (37.80 ± 5.14 points) was larger than the mean of the linear group (32.81 ± 15.74 points), however the variation is still too large to suggest a meaningful difference. However, the within the 'middle' subgroup the difference in score between the AI group (37.80 ± 5.14 points) and random group (63.63 ± 17.06 points) had a significant difference (p=0.048), which supports the hypothesis.

Those who were previously skilled in video games (the 'skilled' subgroup) responded to the program in a very different way. The AI group showed a negative improvement rate on average with a score change of -11.21 ± 27.88 points. Again, the average score improvement of the linear group was larger than the random group. As above, the high variability within this subgroup's data leads to no conclusive evidence. Perhaps the only thing suggested from this subgroup of 'skilled' subjects is that those who played the game with the adaptive AI showed negative learning outcomes, suggesting that the adaptive environment was detrimental to the motor learning. This could be because they were already so adept at playing, that an AI making the game easier under-stimulated them, resulting in decreased level of performance as the experiment went on. This could suggest that such techniques should not be used on individuals who are considered experienced at video game play.

The ‘non-responder’ subgroup also showed a negative improvement within the AI group, with an average score change of -0.133 ± 4.68 points. Again, the linear group had a higher mean score change than the random group with 34.08 points (± 19.42) compared to 14.93 points (±12.17). Here, the difference in score changes between the AI group and the linear group showed a statistically significant difference ($p=0.034$).

Despite the large amount of variation within the data, the results still suggest that the adaptive gaming environment proved least efficient to the motor learning outcomes of users. Furthermore, the existence of small p-values within the sub-group analysis highlights the importance of patient-specific rehabilitation programs. If a program involves neuro-gaming for rehabilitation, a subject should have a specific plan for learning milestones, depending on their familiarity with the video game process.

It is also worth discussing the validity of the AI code used in this study. This code was intended to observe the playstyle of the subject and change the game settings in a way that optimized the player’s ability to achieve a high score and reach the end. Figure 7 shows a gradual increase in overall distance travelled across all subjects. But with no clear control group to compare to, a different way of validating the code must be set in place. In the end, most subjects would never reach the last test in the game, which included passing through several pipes. This method was then deemed as a valuable way of judging the validity of the AI code by testing how much more often AI subjects reached the end compared to the others. Table 8 displays how many individuals in each cohort group ever made it to the end, and also shows how frequently on average those individuals made it to the end during their 20 rounds. Not only did more individuals within the AI group make it to the end than almost both other groups combined, but these subjects also made it to the end almost two times more often than those in the other groups. The fact that those in the AI group reached the end more often than the other two groups suggests that the AI code was effective in making the game easier for the specific player. This also supports the feasibility of writing code within prosthetic limbs controlled by sEMG that adapt to the user for purpose of comfort and ease of use.

Limitations

The results of this experiment were highly variable. As previously stated, the existence of different types of video game players within the subject pool is suspected to be a cause for the variability within the experiment. Another key source of the variability was the use of the Myoband. Even though the Myoband is a sophisticated EMG device, subjects still had difficulty using it to control the game. Despite the diverse set of hand gestures that trigger the Myoband, all of the motions for most individuals required a great deal of muscle contraction. Upon observing all of the subjects play the game, it was clear that many struggled to keep the bird off the ground simply because of the difficulty they had in triggering the Myoband with a detectable muscle contraction. This resulted in a lot of zero values in the data, because subjects couldn't get very far in the obstacle course. This was also made evident when many subjects complained of muscle fatigue during the experiment. Clearly, they were having to contract their muscle very intensely, so they began to focus more on learning the controller than the game itself. However, it is important to note that those seasoned in gaming seemed to have an easier time learning how to use the band given their history in using their hands to adapt to the game's controller in order to play.

Given the large number of zero scores within the data, there was a resultant limitation of small sample size. Despite the seemingly large number of subjects, the lack of non-zero scores per subject resulted in large variation across the sample. Similarly, the game design might have been too difficult, as it was unknown to what degree people would struggle with using the Myoband.

The theory behind this experiment exists on a sliding scale. The more advanced and adaptive the AI code is, the starker the difference one would expect to see across the AI group compared to the other two. Even though the AI code functioned properly, the existence of statistically insignificant results suggests an inherent limitation to the adaptive capacity of the code itself.

Future Research Suggestions

The first major suggestion to be made after this experiment is the improvement of the experiment design. Making the EMG controller easier to use, and having it require less muscle contraction would be crucial for the acquisition of more data, given so many subjects did not complete the course due to difficulty. Additionally, pre-screening could be introduced to separate subject groups into 'gamers' and 'non-gamers' or any other distinction that correctly characterizes two different groups that respond to the same test in different ways. Given these changes, one could also design this same experiment with an easier game. If the general structure of the game were easier, more people could have reached the end and more meaningful data could have been collected for analysis.

This experiment was also meant to serve as proof of concept for application in technologies such as ‘smart’ prosthetic limbs that can be made to adapt to the specific user for the purpose of ease of use. Now that this concept has been tested, another important aspect of this type of code would be the ability of prosthetic limbs being able to transition between two different states depending on the desires of the user. For example, the robotic lower extremity prosthesis could adapt to the specific anatomy of the user in order to recognize the difference between the command to walk or run. It would be interesting to create another experiment similar to the current one but have the game set for two different states that the player would have to signal for, and to use a controller capable of recognizing intended state after a period of adaptation to the player.

Appendix -A

General Description of AI Algorithm

- If last overall score > game before' s overall score = Gsucc +1
- If last overall score < game before' s overall score = Gsucc -1
- If game before's ALT 1 = 0 and last ALT 1 > 0 ----= Gsucc + 2
- If game before's ALT1 = 0 and 2 games before's ALT 1 > 0
    - If 2 games before ALT 1 > last games ALT 1 = Vsucc +1
    - If 2 games before ALT 1 < last games ALT 1 = Vsucc -1
- Game before's ALT1 > 0 and last games ALT1 > 0
    - If game before's ALT 1 > last games ALT 1 = Vsucc + 1
    - If game before's ALT 1 < last games ALT 1 = Vsucc - 1
- If last ALT 1 =0 and game before's ALT1 > 0 = Gsucc -1
- (the same for ALT2 and ALT3)
- If game before's ALT 2 = 0 and last ALT 2 > 0 ----= Gsucc + 2
- If game before's ALT2 = 0 and 2 games before's ALT 2 > 0
    - If 2 games before ALT 2 > last games ALT 2 = Vsucc +1
    - If 2 games before ALT 2 < last games ALT 2 = Vsucc -1
- Game before's ALT2 > 0 and last games ALT2 > 0
    - If game before's ALT 2 > last games ALT 2 = Vsucc + 1
    - If game before's ALT 2 < last games ALT 2 = Vsucc - 1
- If last ALT 2 =0 and game before's ALT2 > 0 = Gsucc -1
- If game before's ALT 3 = 0 and last ALT 3 > 0 ----= Gsucc + 2
- If game before's ALT3 = 0 and 2 games before's ALT 3 > 0
    - If 2 games before ALT 3 > last games ALT 3 = Vsucc +1
    - If 2 games before ALT 3 < last games ALT 3 = Vsucc -1
- Game before's ALT3 > 0 and last games ALT3 > 0

Key
Overall Score - distance travelled
ALT 1 – flat line obstacle
ALT 2 – steeper pyramid obstacle
ALT 3 – flatter pyramid obstacle

Last Game – game that just happened
Game before – game before the

- If game before's ALT 3 > last games ALT 3 = Vsucc + 1
- If game before's ALT 3 < last games ALT 3 = Vsucc - 1
- If last ALT 3 =0 and game before's ALT3 > 0 = Gsucc -1
- If Past three games have improved overall score, but fourth (most recent) game is lower than all = set Vsucc and Gsucc to 0
- If Gsucc = 1 then Gravity is changed by 0
- If Gsucc = 2 then Gravity is changed by -0.025
- If Gsucc = 3 then Gravity is changed by -0.045
- If Gsucc = 4 then Gravity is changed by -0.05
- If Gsucc = -1 then Gravity is changed by 0.1
- If Gsucc = -2 then Gravity is changed by 0.1
- If Gsucc = -3 then Gravity is changed by 0.1
- If Gsucc = -4 then Gravity is changed by 0.1
- If Gsucc > 4 then Gravity is changed by -0.1
- If they passed ALT1 but did not get passed Alt 2
  - If Vsucc =1 then Y velocity is changed by 0
  - If Vsucc < 1 then Y velocity is changed by -1
- If they pass ALT 2 but not ALT 3
  - If Vsucc =1 then Y velocity is changed by -1
  - If Vsucc =2 then Y velocity is changed by 0
  - If Vsucc =-1 then Y velocity is changed by -0.05
  - If Vsucc =-2 then Y velocity is changed by 1.5
- If they pass ALT 3
  - If Vsucc =1 then Y velocity is changed by -1
  - If Vsucc =2 then Y velocity is changed by -0.5
  - If Vsucc =3 then Y velocity is changed by 0
  - If Vsucc =-1 then Y velocity is changed by -1
  - If Vsucc =-2 then Y velocity is changed by -1.5
  - If Vsucc =-3 then Y velocity is changed by -2
  -
- If they pass pipe test then Sweet Spot phase is activated
- **The following are condition within the SWEET SPOT PHASE**
- If last ALT 1 < game before's ALT1 = Ssucc +1
- If last ALT 2 < game before's ALT2 = Ssucc +1
- If last ALT 3 < game before's ALT3 = Ssucc +1
- If last Pipe test > game before's Pipe test = Ssucc +1
- If last ALT 1 =0
  - If last ALT 1 =0 and game before's ALT1 = 0 = Ssucc set -1
  - If last ALT 1 =0 and game before's ALT1 > 0 = Ssucc set 0

- (if the game before the scores are zero, the game looks at 2 games before rather than game before)
- If Ssucc is 0 = don't do anything to velocity
- If Ssucc is 1 = change velocity by -0.0 5
- If Ssucc is 2 = change Velocitychanger by -0.25
- If Ssucc is 3 = change Velocitychanger by -0.5
- If Ssucc is 4 = change Velocitychanger by -1

If Ssucc is -1 = change Velocitychanger by + 0.5

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