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Multi-Gain Control: Balancing Demands for Speed and Precision

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MULTI-GAIN CONTROL: BALANCING DEMANDS FOR SPEED AND PRECISION

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By

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Lucas Warner Lemasters ENTITLED Multi-Gain Control: Balancing Demands for Speed and Precision BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

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ABSTRACT

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Woodworth's Two-Component Theory (1899) partitioned speeded limb movements into two distinct phases: (1) a central ballistic open-loop mechanism and (2) a closed-loop feedback component. The present study investigated the implementation of multi-gain control configurations that utilized separate gain values for each movement phase. A target acquisition task using Fitts' Law (1954) was performed within a virtual environment using three control devices with three gain settings: mono-gain, dual-gain and continuous gain. The gain settings differed by the amount of gain values available to the participant. It was found that dual-gain and continuous gain configurations yielded lower movement times and higher information-processing rates than the mono-gain configurations. The lower gain values presented in the dual-gain and continuous gain configurations were reported to mitigate oscillations around smaller targets that were responsible for additive settling time. Implementation of multi-gain control logic could help improve performance when navigating through large spaces and acquiring small targets.

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

With the advent of virtual simulations, models of human motor control are being stretched to explain the behavior observed when humans interact with these high-fidelity simulations. Models such as Fitts' Law (1954) and Woodworth's Two Component Theory (1899) remain robust in the face of the ever-changing technological landscape. The general principles of manual control that they describe, particularly the presence of speed-accuracy tradeoffs, can be generalized to human-machine systems that involve movement via device input. Conclusions drawn from research in this area have led to guidelines for designing human-machine systems in order to enhance performance.

Innovative new ways of interacting with systems demand and, to an extent, rely on the attention of manual control experts to optimize system control efficiency, safety, and usability. For example, as a result of the popularity of gaming, there are now additional low cost device solutions, such as the Xbox controller, that have been demonstrated by experts to be efficient and sometimes better than traditional input devices (Ardito, Buono, Costabile, Lanzilotti, & Simeone, 2009). In addition to testing new devices, potential methods of enhancing control within devices have been developed and analyzed, particularly for improving performance in target acquisition tasks. This study evaluated the effect of multiple modern input devices and controller gain enhancements on performance in a target acquisition task within a virtual environment.

1.1 Initial Research

Research initially began with a virtual surveillance and target-tracking system developed by the AFRL Human Effectiveness Directorate. The project aimed to create a virtual surveillance workspace in which operators could interact with sensors located in the physical world, performing responsibilities such as tracking targets, monitoring an event for safety, adjusting cameras, and directing ground operations. The virtual environment would directly mirror the actual environment. For example, a section of a large city could be reconstructed in the simulation that included the actual location of multiple cameras, sensors, drones, operators on the ground, etc. Real-time information from the sensors would feed the simulation and operators would use input devices (e.g., mouse, joystick, Xbox controller) to interact with virtual objects in the simulation that corresponded to actual sensors. Performing an action on a virtual object would, in turn, actualize on the physical sensor. For example, a virtual object representing a camera might be selected and rotated by the operator causing the physical camera in the actual environment to rotate accordingly. With a bird's eye view of a location, real-time information, and the ability to adjust sensors, operators could assume a surveillance 'overwatch' position that could improve logistics, allocation of resources, and overall surveillance efficiency.

The challenge in developing such a system is designing it in a way that best supports and compliments human performance. In particular, this involved comparing alternative input devices and alternative algorithms for translating human motion into actions in the virtual environment. The primary goal was to select a device that afforded smooth, time efficient control with a balance between speed and precision. Eventual operators of the system would need to navigate and manipulate objects quickly in order to keep up with potential targets, communicate with ground personnel, and maintain safety.

Research began with a small informal preliminary study carried out to examine several different input devices. Utilizing Fitts' law, a target acquisition task with targets varying in difficulty was used to evaluate the devices on movement time and information-processing (IP) rates. Upon review of the results, it was discovered that adequate performance had not been achieved based on large movement times, low IP rates, and subjective feedback. Informal discussion with participants revealed a difficulty in selecting smaller targets due to cursor oscillation around the target and what they described as "controller sensitivity'. This sensitivity issue was diagnosed as a problem with high controller gain and, as a result, a series of gain-altering configurations were developed to mitigate the problem. Thus, the main focus of this thesis was to evaluate the performance of multi-gain configurations across devices.

1.2 Literature Review

To begin, a literature review examining theories, models, and principles of goal directed speeded limb movement was conducted, starting with Woodworth's Two Component Theory (1899). Stemming from this review, a general framework was drawn and applied to the problem at hand. In search of a solution, a review of target acquisition enhancements including gain manipulations was examined and critiqued. Finally, a developed solution implementing multi-gain configurations is discussed, compared with other enhancements, and fit into the general framework.

1.2.1 Woodworth's Two Component Theory. Woodworth (1899) pioneered early research in manual control by examining speed, accuracy, and movement characteristics in continuous goal-directed voluntary movements (Flach & Jagacinski, 2003). Using a reciprocal pointing task, he was able to measure spatial accuracy, consistency of movements, and spatiotemporal characteristics of limb trajectories (Elliot, Chua, & Helsen, 2001). In his hallmark study, participants made horizontal back and forth movements with a pencil on paper between lines that were a fixed distant apart. This paper was attached to a drum rotating at a constant speed resulting in crude sketches of limb trajectories. They revealed that for initial aiming attempts, the first portion of the limb movement was generally a rapid and uniform approach to the target. However, as distance to the target decreased, movement became slow, broke off into small sporadic adjustments in position, and finally stabilized on the target.

From these observations, Woodworth developed a model of limb control that provided a framework for how simple target-aiming movements were controlled. He suggested that aiming movements are composed of two distinct phases: (1) a central ballistic open-loop mechanism followed by (2) a closed-loop feedback-based component (Elliot, Chua, & Helsen, 2001). In Phase 1, an initial ballistic response maneuvers the limb into the vicinity of the target area. Once in the target region, the limb comes under feedback-based control in Phase 2 where visual information regarding limb and target position is used to make fine adjustments in movement trajectories that result in the acquisition of the target (Elliot, Chua, & Helsen, 2001). Woodworth referred to this as the "homing" phase where "little extra movements" were added or subtracted from the initial impulse to acquire the target (Woodworth, 1899). Figure 1 is an example of velocity trajectories for three separate target acquisitions and provides a good example of how movement phases are partitioned. All three trajectories (*a*, *b*, and *c*) consist of a high velocity initial ballistic movement to get near to the target—characteristic of Phase 1. Trajectories *b* and *c* miss the target and require corrective submovements as indicated by the dashed lines (Phase 2). Notice that trajectory *a* falls directly on the target and does not require submovements for acquisition. Woodworth's theory offers a viable framework for studying human motor control in that it partitions movement trajectories that can be examined under experimental manipulation to analyze performance, characteristics, and potential problems. Because the problem in this study was movement phase specific, Woodworth's Two Component Theory provided an excellent framework.

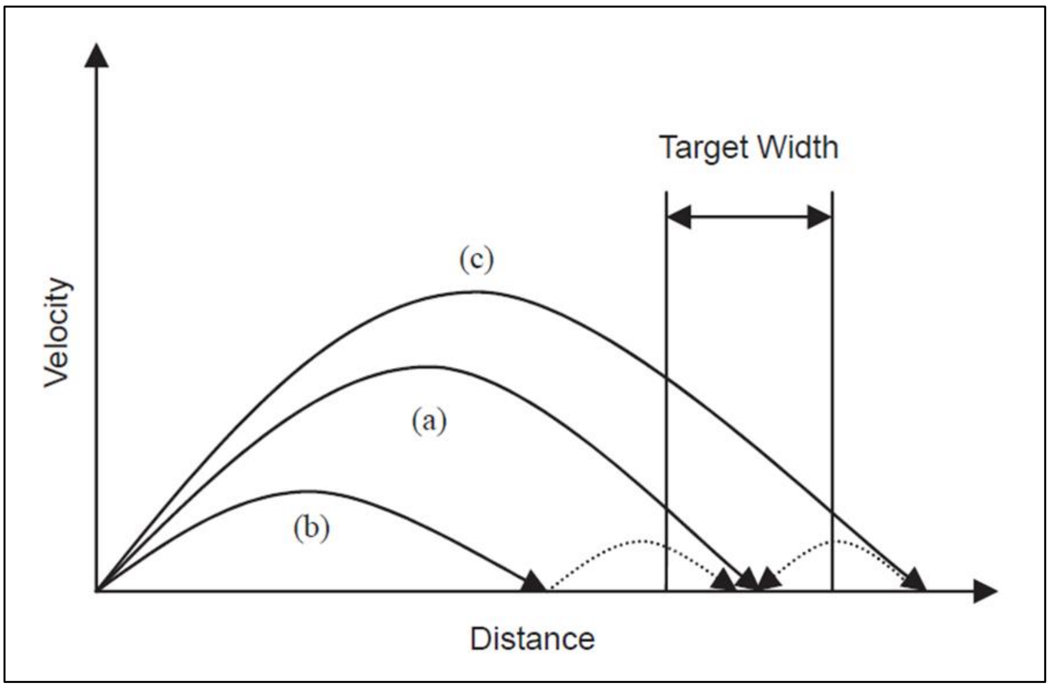


Figure 1. Example velocity profiles of three separate movements aimed at acquiring a target.

1.2.2 Fitts' Law. In the mid-20th century, Paul Fitts studied the speed-accuracy relations of goal-directed movements and, in 1954, developed Fitts' Law—perhaps the most successful, robust human motor behavior model used in Human Computer Interaction (HCI). Extending Shannon's theorem 17 in information theory, Fitts discovered a formal relationship that modeled speed-accuracy tradeoffs in rapid, goal-directed aiming movements (Jagacinski & Flach, 2003). Using a reciprocal tapping task with a stylus, he found that the time to move and tap a target with a specific width (W) and distance (A) is a logarithmic function of the spatial relative error (A/W). The function is as follows: $\boldsymbol{MT = a + b\ \log_2\left(\frac{2A}{W}\right)}$

Where:

- MT is the movement time
- *a* and *b* are empirically determined constants
- *A* is the distance (or amplitude) of movement from the initial start to the target center
- *W* is the width of the target

Mathematically interpreted, Fitts' Law is a linear regression model where *a* is the intercept and *b* is the slope (s/bits). The inverse of *b* (bits/s) is called the index of performance, sometimes referred to as the information-processing rate, and measures the information capacity, or rate, of the human motor system in bits per second for a set of targets and, potentially, as in this study, for a particular input device. Input devices yielding higher IP rates are preferred as they afford the processing of more information at a quicker rate.

The logarithmic term ($\log_2(2A/W + c)$) is known as the index of difficulty (ID). Measured in bits of information, it provides a difficulty value based on the size and distance of the designated target. Fitts found that acquiring targets gets increasingly more difficult as amplitude gets larger and/or width gets smaller. Therefore, targets that are far away and narrow are given a higher ID than those targets larger and closer together. The higher the ID, the longer the predicted time to acquire. Using these indices, a test bed of targets varying in difficulty can be created and used to analyze new control configurations and devices in terms of target acquisition performance. Information-processing rates paired with movement times across varying target ID's provide a solid basis for such an analysis. The configuration or device yielding the lowest movement times and highest IP rates across varying target difficulties is desirable. In the preliminary testing, this procedure was followed. A test bed of targets varying in difficulty (e.g., amplitude and width) was created and mapped to the virtual environment. Multiple input devices were used to acquire targets, movement times were measured to gauge performance, and IP rates were calculated. In general, by means of Fitts' Law principles, an experiment, such as the preliminary, can be designed where the goal is to find the most efficient input device and/or configuration. This same format was followed for the main formal study.

One observation from the preliminary testing results, as mentioned before, was the difficulty in selecting small targets in the environment due to excessive oscillation. Participants reported having extreme difficulty in getting the cursor to settle in on the smaller targets, particularly at larger amplitudes. They found themselves overshooting the target multiple times until they finally ‘nudged’ it into place. Movement times supported this claim as they were longest for the smaller targets with higher ID’s. In terms of Woodworth’s Two-Component Model, this makes sense. The larger the distance that needs to be covered and the smaller the target, the greater time it takes and the greater the endpoint variability requiring more corrective submovements for acquisition. Continuing on, we turn to the research done in the latter half of the 20th century attempting to explain the underlying mechanisms of limb movements and their associated speed-accuracy relations founded by Woodworth and Fitts.

1.2.3 Other Models of Goal-Directed Movement. *1.2.3.1 Iterative-Corrections Model.* Since Woodworth and Fitts, other models of human motor behavior have been developed to explain for the observations in goal-directed target acquisition tasks. The first processing-based model to build on Woodworth’s two-component model of limb control was the *iterative corrections* model proposed by Crossman and Goodeve (1983) and later refined by Keele (1968) (Elliot, Chua, & Helsen, 2001). The model explains the relation between speed and accuracy in reciprocal aiming as illustrated by Fitts’ Law. It attributes the observations entirely to a closed-loop feedback control in which consecutive discrete movements are made in response to feedback indicating whether the target has been attained. In other words, rather than separate ballistic and feedback phases, movements are composed of consecutive ballistic phases that are prepared based on visual feedback obtained from the previous movement. Error associated with each submovement is proportional to the remaining distance to the target with each subsequent movement having less error as they covered smaller distances. Therefore, the final accuracy and movement time is dependent on the number of corrective movements with the limiting factor being the time required for visual feedback to operate, approximately 200 ms (Keele & Posner, 1968). However, though mathematically sound, kinematic evidence obtained from high-speed film (Langolf, Chaffin, & Foulke, 1976) suggested that there are not discrete changes in limb trajectory at any fixed time interval. Thus, the iterative corrections model was abandoned (Elliot, Chua, & Helsen, 2001).

1.2.3.2 Single-Correction Model. Beggs and Howarth (1970, 1972; Howarth, Beggs, & Bowden, 1971) proposed the *single-correction* model of speed-accuracy relations. This model, similar and to some extent indistinguishable from Woodworth's two-component model, included an initial ballistic movement that got the limb into the vicinity of the target where a single correction was made based on visual feedback. Accuracy of the movement was dependent on the proximity of the limb to the target when the correction was initiated. The only difference between the single-correction model and Woodworth's model is the distinction between a single programmed correction versus the visual homing that Woodworth described in the second phase.

1.2.3.3 Impulse Variability Model. Schmidt, Zalaznik, Hawkins, Frank, & Quinn (1979) postulated another explanation called the *impulse variability* model that did not include a feedback-based corrective process. It attributed observations in Fitts' Law almost exclusively to an initial ballistic impulse initiated by the muscles that flung the limb towards the target. The model held that the force used to move the limb increased proportionally with the absolute force required for movement. Endpoint variability increased with force, thus smaller targets require smaller forces—leading to slower movements. In terms of Woodworth's model, this process only pertained to the initial impulse phase whereas force variability determined the extent to which secondary feedback-based corrective processes needed to operate (Elliot, Chua, & Helsen, 2001).

1.2.3.4 Optimized Submovement Model. The most widely accepted and influential model of the last twenty years (Rosenbaum, 1991) comes from Meyer et al. (1988) and is called the *optimized submovement model*. This model was developed to account for speed-accuracy relations in tasks in which participants terminate their movements within a target while maintaining minimal movement time. The model holds that “movement production is characterized by an optimal compromise between (a) the greater neuromotor noise and potential endpoint variability associated with a more forceful movement and (b) the time-consuming requirements of corrective submovements” (Elliot, Chua, & Helsen, 2001). The primary ballistic phase and secondary corrections phases are combined to minimize overall movement time while still meeting accuracy requirements. A normal distribution of ballistic endpoints around the intended target occur over a series of aiming attempts as a result of stochastic noise in the motor system. When the ballistic endpoint falls outside of the target area, a secondary corrective submovement is carried out unchanged by feedback until it is completed. The model is able to account for movements of short and long duration because of the integration of both the impulse variability and feedback-based corrective processes—the best of the impulse variability and iterative correction models.

Furthermore, kinematic evidence suggests that velocity profiles of movements are affected by the demands of accuracy, or the size of the targets. For large targets, profiles are generally symmetrical as a result of requiring very few subsequent corrective movements. On the other hand, a number of investigators have shown that decreasing the size of the target results in changes to the shape of the velocity profile (Elliot, Chua, & Helsen, 2001). For smaller targets, participants spend a greater proportional time after peak velocity because additional time is necessary to process and use visual and kinesthetic feedback to moderate deceleration and/or make corrective submovements. These kinematic observations are consistent with Woodworth's two-component model, but are inconsistent with the assumptions of the optimized submovement model which posits that profiles for the initial impulse movement and the subsequent corrective movements are symmetrical. In reality, the initial impulse portion of the movement is more fixed than the latter. For the second portion of the movement, asymmetrical discontinuities are often present in the deceleration profile indicating adjustments made to the movement based on feedback, particularly if accuracy requirements are high.

The optimized submovement model is similar to Woodworth's model but with a more sophisticated dual-process explanation. Nonetheless, it maintains the framework that Woodworth established and provides the best contemporary description of speed-accuracy relations in goal-directed aiming—but with a few amendments. For one, there is empirical evidence to suggest that the distributions of primary movement endpoints are not equally distributed around the middle of the target. The initial ballistic movement minimizes the temporal costs associated with error by tending to undershoot the target rather than overshoot (Guiard, 1993; Elliot, Carson, Goodman, & Chua, 1991). Overshooting targets is more time-consuming and requires additional attentional resources because the limb travels a further distance, has to overcome inertia to make a reverse movement, and requires a switch of muscles groups. Therefore, the distribution of movement endpoints tend to be centered around a location short of the target where undershoots occur, a few extending beyond the target, and ideally some centered on the target itself (Barrett & Glencross, 1998; Guiard, 1993).

The second amendment that needs to be considered is the change that occurs over practice. There is evidence that humans have awareness of the inherent variability of particular movements and, over time with practice, can adjust their movements to minimize time while maintaining accuracy (Elliot, Chua, Pollock, & Lyons, 1995). That is, after repeated attempts, the performer develops a central representation of the pattern of muscle activation needed to acquire the targets (Keele, 1968; Schmidt, 1976). The initial impulse of the movement becomes more forceful as the performer discovers how close they can get to the target without overshooting it, leading to a decrease of secondary corrective submovements.

1.2.4 Speed-Accuracy Imbalance. If we apply the general framework of the models Woodworth (1899) and Meyer (1988) developed, we can begin to piece apart the problems observed in the preliminary study. Problematic oscillations around the target resided in the secondary phase of the movement where corrective submovements occur. Despite feedback-based control, participants failed to control the cursor accurately enough to the make the necessary submovements for acquisition but succeeded in quickly getting to the target vicinity. Movement times were prolonged and performance was deemed inadequate. Participants reported that the cursor "moved too fast" and was "overly sensitive" in response to input on the device, leading to a difficulty in getting the cursor to settle on a target. Based on the oscillations explicitly present in the secondary phase as well as the subjective feedback from participants, it was hypothesized that the controller gain setting was to blame.

In our case, the gain level, the ratio of the output signal to the input signal amplitude (usually labeled as “sensitivity” in most device options, i.e., a computer mouse or video game controller), was interacting with arm dynamics to differentially impact the speed-accuracy tradeoff and hinder performance. While high gains tend to emphasize cursor speed, low gains aid in target accuracy. In terms of movement phases, high gains are usually only helpful in the initial ballistic phase where they can decrease the time needed to get to the target vicinity by increasing the ratio of output distance to the physical distance a limb needs to cover. Conversely, low gains are helpful in the homing or settling phase where precise movements need made over a small distance. Observations revealed a high gain setting having an adverse effect on the settling phase of the limb movement. Although participants could quickly maneuver the cursor to the vicinity of the target, they were unable to steady it onto the target. They could not scale down their physical limb movements to match the needed distance to target, resulting in oscillation and target overshoots. Thus, an uninformed high gain setting resulted in poor performance far from the peak performance found by researchers emphasizing a speed-accuracy compromise.

In this study, an attempt was made to mitigate excessive oscillations in the secondary phase of goal-directed aiming by not only readjusting the gain value but also by adding and manipulating the availability of different gain values in hopes of enhancing performance beyond that of a compromise. Before going into detail about the configurations and gain logic implemented, we will review literature that has attempted other means of target acquisition enhancement.

1.3 Target Acquisition Enhancements

Numerous attempts have been made to enhance performance within workspaces involving target acquisition. Display functionalities and tools can be developed and/or altered to adjust speed-accuracy operating characteristics. There have been attempts to "beat" Fitts' Law with the aid of artificially reducing target distance, increasing target width, or both (Balakrishnan, 2004). Enhancements primarily reducing distance include organizing menus in a way that minimizes distance from the target to the cursor (e.g., linear vs. pie menus) (Callahan et al., 1988) or temporarily bringing targets to the cursor (Baudisch et al., 2003). However, in many interfaces, menu redesign and transformation is impractical and difficult, particularly when the nature of the environment (in our case virtual) is not receptive to menus. Likewise, temporarily bringing the targets closer to the cursor produces a lot of clutter, particularly when multiple targets are in the vicinity, and only proves itself useful in sparsely populated interfaces (Balakrishnan, 2004).

Enhancements aiming to facilitate performance by increasing target width include input filtering (Vogel & Balakrishnan, 2005), area cursors rather than pointer cursors (Tse, Hancock, & Greenberg, 2007; Kabbash and Buxton, 1995), and expanding targets (Furnas, 1986; Mackinlay, Robertson, & Card, 1991; Bederson, 2000). Kabbash and Button (1995) showed that area cursors with larger widths could improve performance in target acquisition tasks. In terms of Fitts' Law, they exchanged target width for cursor width. In this way, the high index of difficulty that is typical of smaller targets was reduced when selected by a cursor with a larger width. However, a significant problem with area cursors is that large cursors obscure underlying parts of the interface and make it difficult to select targets that are in close proximity of one another (Worden, Walker, Bharat, & Hudson, 1997).

Expanding target techniques have been developed where the size of the viewing region on the interface dynamically changes to produce a larger target area for the user to interact with. McGuffin and Balakrishnan (2002) examined these techniques and concluded that they were effective in facilitating, not the initial ballistic movement, but the subsequent secondary submovements as operators are able to respond to the changing size of the target via closed-loop feedback control. They hypothesized and confirmed that, in terms of Fitts' Law, it was the final expanded size of the target that dictated movement time. Overall performance then could be accurately modeled by Fitts' law using the expanded target width as the size parameter. While this technique did improve performance, it was not generalizable to scenarios involving multiple targets. When multiple targets were in close proximity, expanding one target affected neighboring targets such that they were occluded or pushed out of the way. Such effects had implications for performance and undesirable side effects. Lee, Kwon, & Chung (2012) examined target expansion techniques (occlusion and push) along with expansion areas (none, single icon, fish-eye, and group) thought to be compatible with multiple targets. However, they did not find significant differences in performance speed and only trends in terms of accuracy. It is unclear whether the expanding target technique is of practical use.

Similar to the expanding target techniques, Flach, Hagen, & O'Brien (1990) examined performance in a single axis discrete positioning task using three different mappings for the visual display of the movement space. Display distance to actual distance was matched or proportioned to magnify the space containing the target using a split-screen and logarithmic mapping. The thought was that performance would increase for smaller targets in the magnified conditions. Evidence suggested that for precise movements, fewer 2nd phase corrective movements were required for smaller targets in the split-screen condition. However, there was difficulty in operating nonlinear displays that outweighed the magnification advantage. Thus, the authors recommended that linear displays be used when possible and that gain be examined as a manipulation.

The majority of target acquisition enhancements have been only moderately successful in their appropriate setting, but limited in their generalizability, applicability, and robustness. Enhancements aimed at reducing distance often require a complete redesign of the interface or cluttering dynamics. Likewise, those techniques that artificially reduce width, such as area cursors and expanding targets, occlude important information, make it hard to select clustered targets, and spatially distort the environment in undesirable ways. Lastly, some techniques, such as magnification of the target area, introduce nonlinear displays that increase the difficulty of operation.

1.4 Control-Display Gain Manipulations

Control to display gain can be used to enhance performance in target acquisition scenarios and it will be the manipulation of choice in this study. Gain can be thought of as the ratio of the output signal to the input signal amplitude. For example, adjusting the sensitivity of your computer mouse is an adjustment of gain. If you set a higher gain, smaller movements of the physical mouse yield much larger cursor movements on the screen. Conversely, if a lower gain is set, small movements of the physical mouse will yield smaller cursor movements on the screen. The effect of gain on performance has been extensively explored (Buck, 1980; Arnaut and Greenstein, 1990; Kwon, Choi, &

Chung, 2011). In general, it is agreed upon that excessively high gains result in poor performance due to the difficulty in making precise submovements at the end of a movement despite being able to navigate quickly to the target vicinity. Conversely, excessively low gains improve performance within the second phase of the movement where precise corrections are needed, but at the cost of a lengthy initial movement. In terms of operating a computer mouse, you do not want to waste time overshooting icons because of a high gain, nor spend too much time guiding the cursor around with a low gain.

For two-component based control systems such as operating a mouse, the standard has been to pick a gain that compromises between speed and precision (Kantowitz & Sorkin, 1983). Similarly, investigations using reaction times such as Fitts (1966) and Rabbitt (1981) have concluded that performance efficiency reaches a maximum threshold at some middle of the road, intermediate speed-accuracy setting (Wickens, Hollands, Banbury, & Parasuraman, 2013).This tradeoff results in a U-shaped gain-performance curve where optimal performance is achieved at a moderate gain (Gibbs, 1962). Figure 2 illustrates the compromise between gain and quality of performance. Low gains are Phase 1 limited in that they slow down the ballistic portion of the movement, taking longer to get to the vicinity of the target, but allowing more precise submovements in Phase 2. High gains yield unstable performance and are Phase 2 limited in that although they can quickly get in the target vicinity, there is an inability to make precise submovements for acquisition. Therefore, a moderate gain is required to meet adequate performance as it affords enough speed to get in the vicinity, but not too much whereas submovements are infeasible.

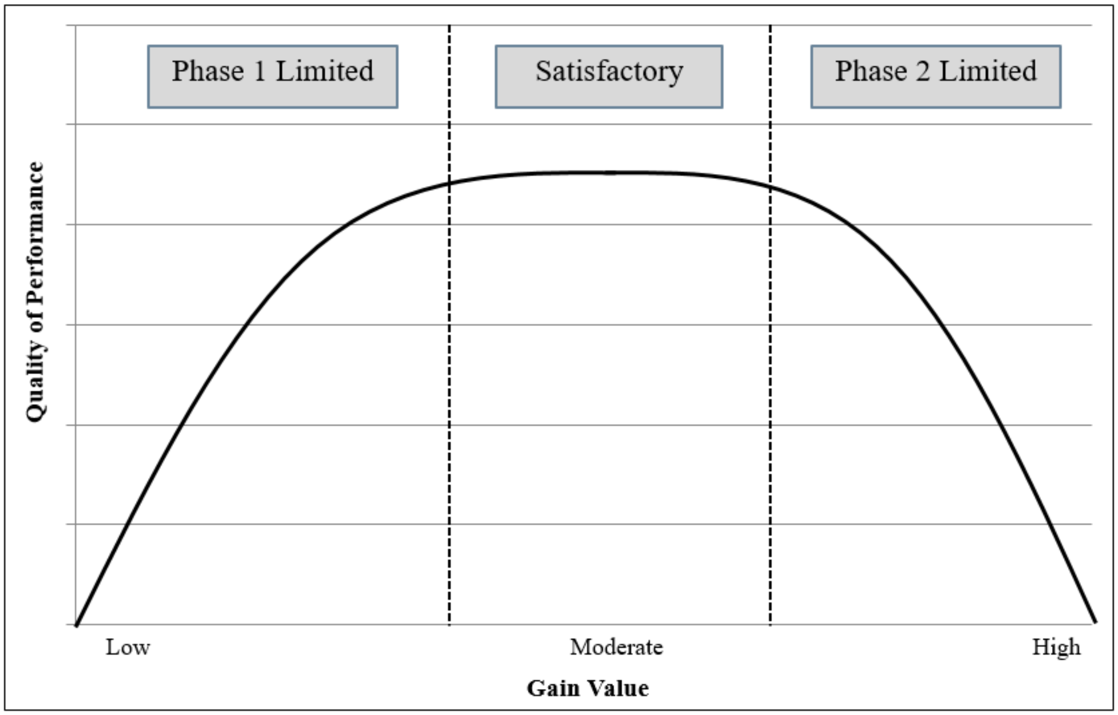


Figure 2. U-shaped Gain-Performance Curve. Depicts the impact of increasing gain on performance.

Researchers have tried to get around the gain-performance tradeoff by developing performance-enhancing techniques. One such technique dynamically adjusts gain based on knowledge of the target. Gain is increased when the cursor is outside of the target and decreased when inside the target, resulting in “sticky targets” (Balakrishnan, 2004). Worden, Walker, Bharat, & Hudson (1997) and Keyson (1997) demonstrated that the use of sticky targets resulted in significantly decreased target acquisition times. However, such a technique is designed for single isolated targets. Problems arise when the space is crowded with multiple targets that are in in the way or along the same line as the desired target. Performance may degrade as the user is slowed as they move over them in order to get to the desired target. However, anticipating this problem, Worden, Walker, Bharat, & Hudson (1997) proposed a solution drawing off of the optimized submovement model

(Meyer et al., 1988). He suggested that gain should remain high during high-velocity initial movements even when over potential targets. In this way, as long as users moved quickly over undesired targets, they could effectively skip them without a performance cost. It was effectively demonstrated that performance was unaffected by the distractor target and such a technique was viable, but it has been noted that distractor targets close to the desired target may be more difficult to skip over considering the user would start to slow down in preparation for more precise corrections. Distractor targets in this instance might make corrective movements more difficult.

1.5 Multi-Gain Control Logic

The techniques examining performance enhancing gain manipulations have largely been automated. That is, manipulations are embedded within the system and activated involuntarily when coded to do so. It appears that these sorts of enhancements have largely been unsuccessful with the majority of them yielding compromises of speed or precision and an inability to dichotomize when manipulations should occur. In the present study, we address these shortcomings and attempt to develop a worthwhile performance enhancement by examining each of the two movement phases—open-loop ballistic and closed-loop corrective submovements—and independently optimizing their gain values based on stability constraints. A high gain is appropriate for the open-loop ballistic phase as it will get to the target vicinity faster. A lower gain is needed for the closed-loop submovement mechanism to emphasize precision and make fine adjustments. This multi-gain logic was implemented in two different configurations that will be discussed in detail later in this paper. In this manner, neither speed nor precision are compromised as users will have access to two independent gains designed to address each phase of the movement. Furthermore, to avoid erroneous automation that limits the user, gain manipulations will be left to the discretion of the user and activated voluntarily. Independent gain values for each movement phase that are activated voluntarily should afford a more accurate, time efficient control system for target acquisition.

1.6 Preliminary Testing

Preliminary testing supported this notion of multi-gain logic. In a condition using an Xbox controller with a single gain value (mono-gain), it was found that the gain value was set too high for the secondary closed-loop control phase. Participants could not get the cursor to stop oscillating and settle in on the smaller targets. They lacked the necessary precision to complete the task in a timely manner. Movement phases could no longer be efficiently controlled separately via the device. However, once a “dual-gain” configuration was implemented in an Xbox controller where users had access to two different gain values (low and high), vast improvements in performance were observed as well as diminished oscillations. Instead of having a single “optimal” gain, we introduced two different gain values for each movement phase that could be used at the discretion of the user. Based on this finding, we decided to further explore multi-gain enhancements across devices.

Based on the success of the dual-gain configuration, another multi-gain configuration was implemented—continuous gain. Instead of having two discrete gain values, the continuous gain configuration gave users access to a range of gains (low to high) that could be controlled via controller displacement. The idea behind this implementation was to (1) allow users to select a gain that was suitable/comfortable for them based on individual differences and (2) “smooth” the gain-changing phase whereas instead of an abrupt switch between two very different gain values, there would be a gradual transition from high to low gains as the participant glided toward the target producing a smooth acquisition, reducing the necessary number of submovements, and preventing overshoots.

The purpose of this experiment was to expand on preliminary findings in terms of multi-gain control. The performance of three continuous movement devices, each with three gain configurations, was examined. The three gain configurations used were (1) mono-gain, (2) dual gain, and (3) continuous gain. The three devices used were a (1) Xbox 360 Controller, (2) Samsung Slate Tablet, and (3) THRUSTMASTER Hotas Warthog Joystick and Throttle. It was hypothesized that the multi-gain configurations (dual and continuous) would yield better performance than the mono-gain configuration based on gain values independently optimized for each movement phase. The transference of multi-gain control logic to each device was also examined. Subjects used each device with every gain configuration to complete a series of target acquisition tasks in a virtual environment.

2. METHOD

2.1 Participants

A total of five participants working for Wright Patterson Air Force Base in Dayton, Ohio participated in the study. They ranged in age from 23 to 36 years with a mean age of 28 years (*SD* = 6.3). All of the subjects were from the Human Effectiveness Directorate and worked in joint partnership with Wright State University on this project. Participants were not offered monetary compensation and voluntarily participated. All participants were required to have fully functioning motor abilities, normal or corrected-to-normal colored vision, and depth perception. Sample size was limited by base access, security clearance, and technical assistance.

2.2 Task and Apparatus

2.2.1 CAVE Environment and Landscape. The study took place inside a cave automatic virtual environment (CAVE). The environment was constructed of six vertical projection walls encircling the user in a 360 degree manner and four overhead projection panels. For this study, only half (180°) of the cave environment was used—three frontal projection walls and two overhead panels—to cut down on target search time. A gridded virtual landscape was displayed in front of the participant as shown in Figure 3. Pictured is a sample target (red sphere) along with a home button (red disc) that was used to initiate trials. Geometrical shapes were used as additional depth cues.

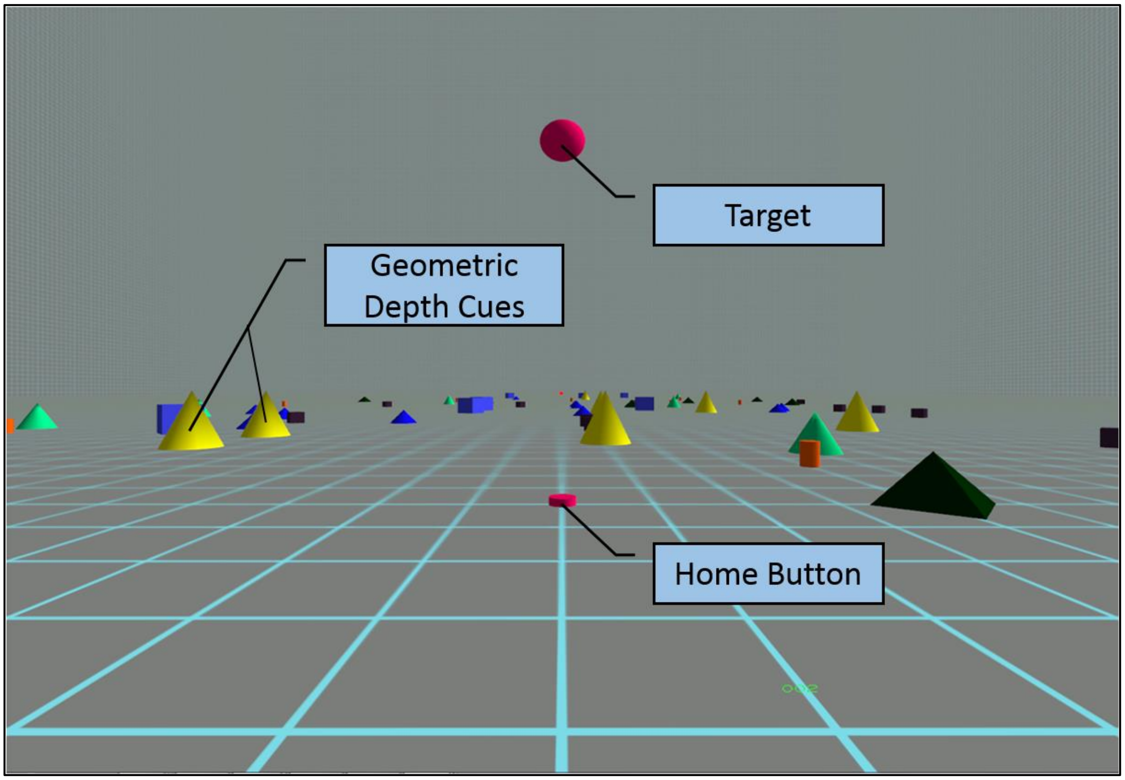


Figure 3. Target acquisition landscape.

2.2.2 Target Parameters. 300 spherical targets of different widths and distances were systematically scattered around the space at varying angles of azimuth and elevation. Target parameters were chosen to cover the entirety of the virtual area and varied in difficulty. Every possible target combination within a 5x4x5x3 design was used (5 distances from button, 4 target widths, 5 horizontal angles, and 3 vertical angles) for a total of 300 different targets. Table 1 shows the breakdown of target parameters. Targets were presented one at a time in a random order throughout each session.

Table 1
Target Parameters

Distance from Button (m)	Target Width (m)	Horizontal Angle (Degrees)	Vertical Angle (Degrees)	Total Targets
10	0.75	-60	0	
20	1	-30	30	
40	2	0	60	
60	3	30		
70		60		
5 X	4 X	5 X	3 =	300

2.2.3 Devices and Gain Configurations. Three devices were used: a wireless Xbox 360 controller, Samsung Slate Tablet, and THRUSTMASTER Hotas Warthog Joystick and Throttle (Figure 4). Three gain configurations were implemented on each device: mono-gain, dual-gain, and continuous gain. Depending on the configuration, gain values available to participants ranged from low to high values. An initial gain value for each device was deemed acceptable based on preliminary configuration test-runs. The mono-gain configuration was fixed at the high gain value. For the dual gain configuration, only the low and high gain values were available and could be toggled back and forth using the device mechanisms. For the continuous gain configuration, the whole range of values from low to high were available and could be scanned as a function of controller displacement (i.e., slowly depressing or releasing the Xbox trigger).

Figure 4. Xbox 360 Controller, Samsung Slate Tablet, and THRUSTMASTER Hotas Warthog Joystick and Throttle.

For the Xbox controller, the left thumbstick maneuvered the cursor around the screen. The left trigger served as the gain adjustor. Depressing the trigger gave access to the secondary gains. For the dual-gain, pressing and holding the trigger activated the lower gain. For the continuous configuration, gain was proportional to trigger displacement. As the trigger was depressed, the gain was lowered.

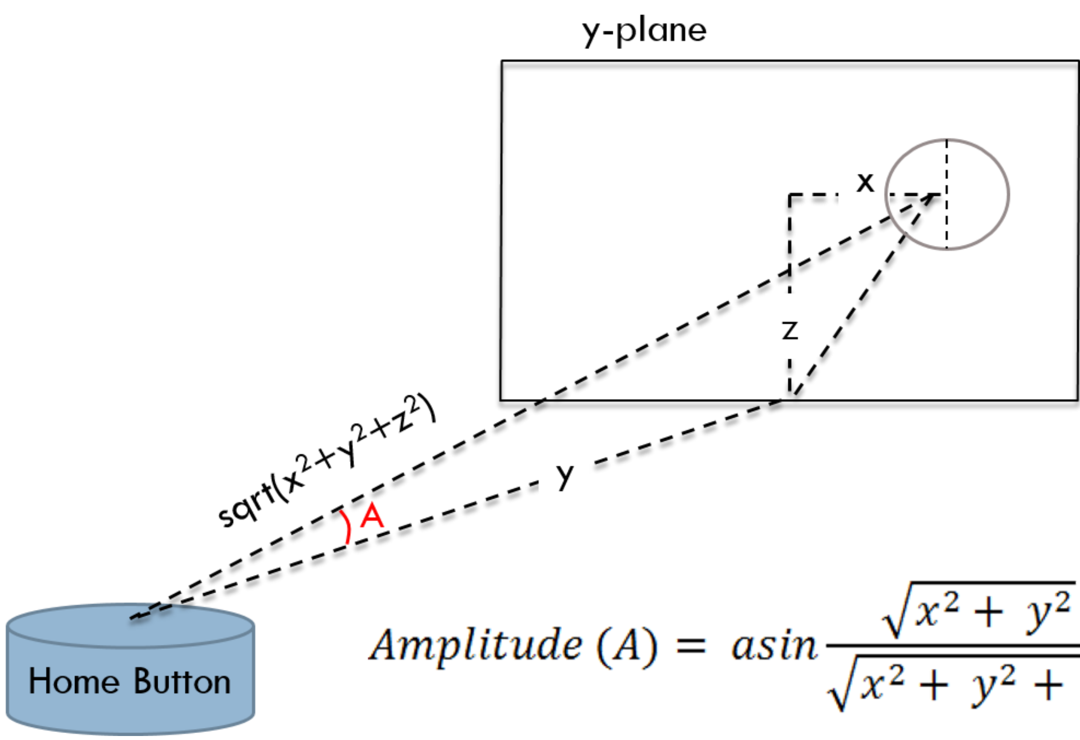
The Samsung Slate tablet had a first-order control scheme. A center crosshair was implemented at the intersection of four quadrants on the tablet display. Participants were required to drag their finger outward in any direction from the crosshair in order to move the cursor position. The three gain configurations were set up as follows: (1) Mono-gain—fixed at high gain value; (2) dual-gain—a button on the tablet display toggled between the lower and higher gain; (3) continuous gain—a sliding scale adjusted values within the set parameters.

For the joystick and throttle, one hand was used to manipulate gain values on the throttle while the other hand was used to maneuver the cursor via the joystick. For the dual-gain, pushing the throttle to the most forward position initiated the lower gain while the opposite executed the highest gain. For the continuous gain setting, gain was adjusted propotionally form low to high with throttle displacement. Gain decreased as the throttle was pushed forward and increased as it was brought back to the resting position.

2.3 Measures

A broad testbed of targets was created that varied in indexes of difficulty (ID). Amplitude was measured as the angle of displacement from the home button to the target.

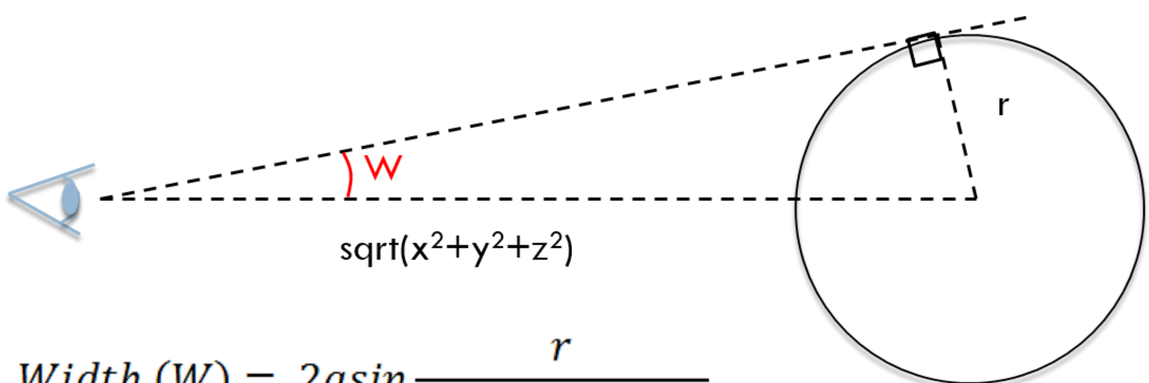
Figure 5 depicts calculation and geometry of the amplitude measurement. This angular measurement was favored over a Euclidean style of measurement due to the fact that acquiring the targets was more like operating a laser-pointer, or *distal pointing*, rather than actually reaching out in space to 'touch' the target. We confirmed that angular measurements were a better fit for the model than Euclidean by comparing R^2 values between the two. In addition, this metric followed suit with previous successful human motor behavior studies involving device pointing such as Kopper, Bowman, Silva, & McMahan (2010). The fidelity of the virtual environment was enhanced with this type of measurement as it mimicked the natural difficulty of selecting a target that is further away. For example, it is much harder to shine a laser pointer on the moon than it is on the side of a nearby barn. As the desired target gets further away, small movements in the wrist and laser pointer become larger movements on the corresponding end such that, in the moon's case, it could translate to thousands of miles.



$$Amplitude\ (A) = asin \frac{\sqrt{x^2 + y^2}}{\sqrt{x^2 + y^2 + z^2}}$$

Figure 5. Calculation and geometry of amplitude metric used in creating targets and analyzing performance.

Width was measured as the visual angle from the center of the target to the outside tangent. Figure 6 depicts the calculation and geometry of the measurement. An angular form of 'width' was needed to match the unit of measurement in amplitude. Therefore, visual angle was appropriate for measuring the widths of targets that differed in distance and diameter. Movement times for each target acquisition trial were recorded and looked at as a function of amplitude and width. To ensure that performance linearly matched the difficulty levels of the targets generated, a few sessions were run with all of the targets and data was collected. As expected, movement times were longer for smaller, more distant targets.



$$Width\ (W) = 2asin\frac{r}{\sqrt{x^2 + y^2 + z^2}}$$

Figure 6. Calculation and geometry of width metric used in creating targets and analyzing performance.

Information-processing rates (bit/s) were computed for each session by plotting indexes of difficulty as a function of movement time for each trial. The slope of the 'line of best fit' for each of these plots effectivly became information-processing rates. This rate was informative of the relative difficulty for each session. It was a global measure of how well the device performed across the 300 trials. This rate along with movement time parameters was the basis for comparison across devices. R^2 values for these plots were recorded and used to convey goodness of fit for the model. Figure 7 is an example depiction of movement time plotted as a function of index of difficulty for a single session with the Xbox controller and continuous gain configuration. The slope of the regression line—the IP rate—as well as the R^2 value is displayed.

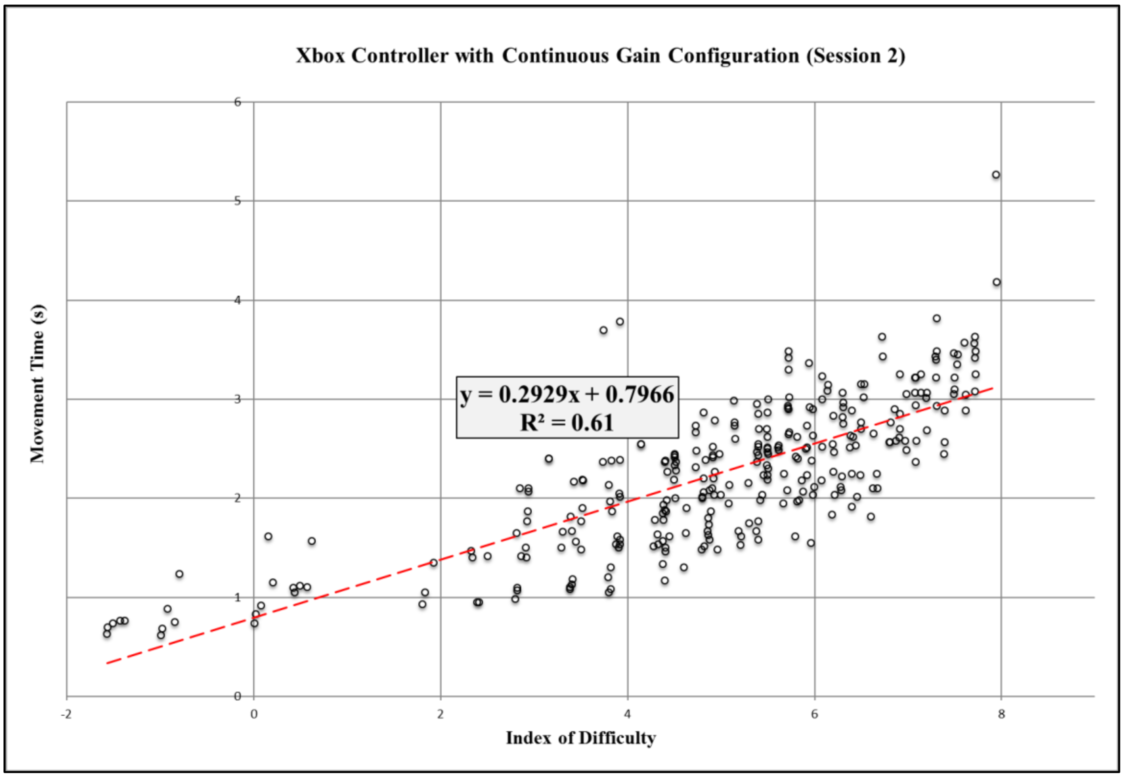


Figure 7. Movement time plotted as a function of index of difficult for one session with the Xbox controller and continuous gain configuration.

Originally, the idea was to record and graph cursor position and gain as a function of target type to evaluate cursor trajectories and gain usage, looking for positional (i.e., undershoots, overshoots, linearity, etc.) and gain differences amongst targets of varying widths and amplitudes. Unfortunately, due to miscommunication, target type was not recorded. Due to this error, cursor position and gain value entries were recorded for the entire session with no notion of which entries pertained to which target. However, gain histories across each session were still used to analyze gain configuration usage.

2.4 Procedure

Participants were seated in front of the virtual display. The control mappings and gain configurations for the device at hand were explained. After being briefed about the device, participants were given instructional steps related to the task: (1) visually search and locate the target; (2) activate the stationary home button at the bottom of the display using the cursor; (3) immediately drag the cursor onto the target, wait for it to turn yellow, and disappear to acquire; (4) repeat. Activation of the home button was used to start recording of movement time and selection of the target stopped the timer.

The explanation of control mappings and gain configurations included brief instructions on how gain configurations were designed to be used. For the mono-gain, participants were told only one gain was available and to do their best to acquire the targets using each device. For the dual gain condition, it was suggested to participants that the lower gain could be used in order to get more precise control for acquiring small targets (i.e., to avoid oscillations). For the continuous gain condition, it was suggested to participants that lower gains might allow finer control in acquiring small targets. Participants were encouraged to use the alternative gains to improve their speed and accuracy.

2.5 Design

Ten practice acquisitions were administered in order to get the participants accommodated to the task, device, and gain configuration; 300 recorded trials followed. Participants ran through nine conditions (3 devices x 3 gain configurations) twice for a total of 18 sessions. Each session took place at intervals of at least fifteen minutes to several days apart. Movement times (s) were measured as the time from home button activation until target selection. Min, max, and mean movement times for each session were recorded for further analysis as well as time histories for gain manipulations and cursor position.

3. RESULTS

Four 3 x 3 x 2 within-subjects repeated measures ANOVA's were conducted. The first factor was device, the second was gain configuration, and the third was session. An ANOVA was done for each of the following: (1) mean movement times, (2) mean minimum times, (3) mean maximum times, and (4) mean information-processing rates. In addition, an analysis of gain usage was carried out by binning gain values into ranges and evaluating percentage of use for each session across devices and configurations. Figure 8 shows movement time parameters (average minimum, mean, and average max movement times across participants) for each session for each device/gain configuration pair.

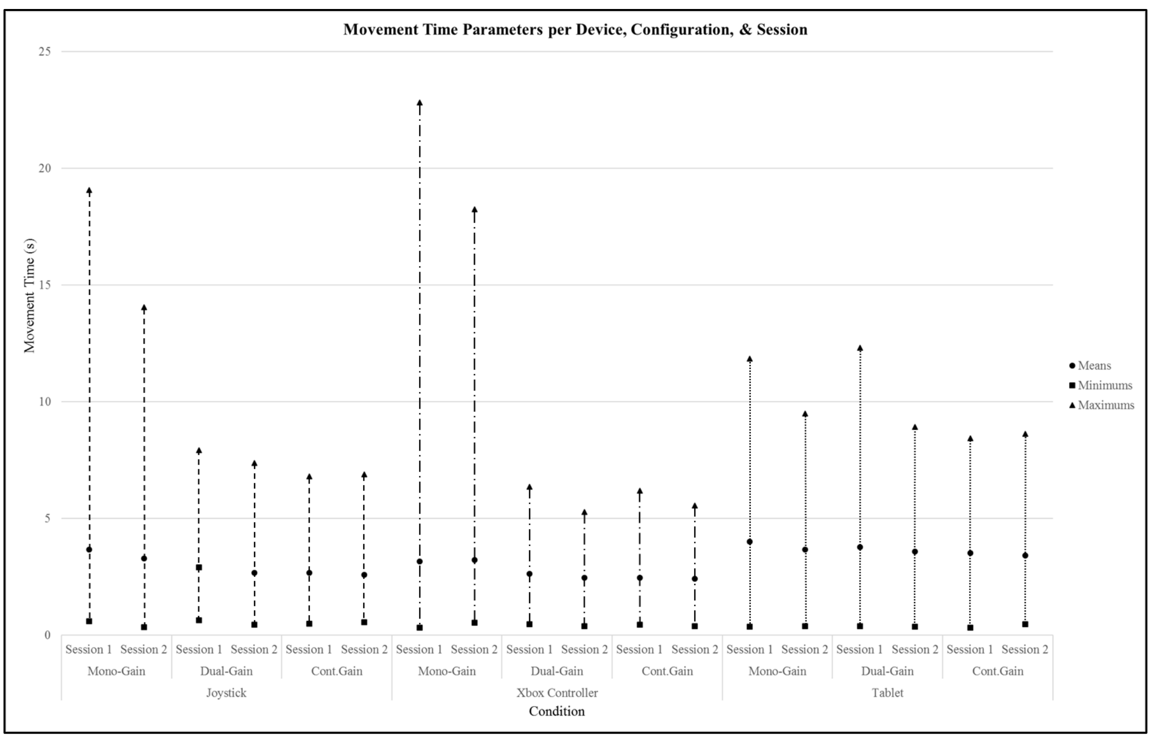


Figure 8. Mean movement time parameters (seconds) across participants for device, configuration, and session.

Mean movement times were calculated for each session for each device/configuration combination and analyzed using a within-subjects repeated measures analysis of variance (see Appendix A). There were significant main effects for device ($F(2, 8) = 25.953$, $p < .05$), gain configuration ($F(2, 8) = 13.197$, $p < .05$), and session ($F(1, 4) = 676.551$, $p < .05$). Pairwise comparisons for device revealed that both the Xbox controller ($M = 2.73$, $SD = 0.50$) and joystick ($M = 2.97$, $SD = 0.64$) yielded significantly lower mean movement times than the tablet ($M = 3.66$, $SD = 0.51$) but were not significantly different from each other. The joystick and Xbox controller, having similar mechanical operating characteristics, were not significantly different from each other. However, the tablet, operating via a touch-based input, yielded significantly worse performance than the other two devices. This performance deficit is believed to be a result of foreign operating characteristics as most touch-based devices involve selecting icons or targets directly with the finger, not by guiding a cursor to the target. Other concerns regarding touch-based input will be discussed later.

For the main effect of gain configuration, pairwise comparisons indicated that both the dual-gain ($M = 3.00$, $SD = 0.60$) and continuous gain ($M = 2.85$, $SD = 0.53$) configurations were significantly better than the mono-gain ($M = 3.50$, $SD = 0.73$) and the continuous gain was significantly better than the dual gain. Although gain configurations were mainly implemented to mitigate excessively long movement times stemming from smaller targets, significant main effects for gain configuration within mean movement times were also expected. The dual and continuous gain configurations enabled users to lower maximum movement times which also lowered mean times. The actuality of difference between the dual and continuous gain configurations will be discussed later in the gain usage section. Session 2 (M = 3.04, SD = 0.65) movement times were significantly lower than Session 1 (M = 3.20, SD = 0.69). It was expected to see significant performance differences from session to session as users became familiar with operating different devices and gain configurations.

There was also a significant interaction between device and session ($F(2, 8) = 8.620$, $p < .05$). Performance with the Xbox controller remained virtually flat from session 1 to session 2 with a mean difference of only 43.3 milliseconds whereas the joystick and tablet saw more substantial improvement with mean differences of 227.2 ms and 214.2 ms respectively. Participants might have had previous experience with the Xbox controller considering it's a popular commercial product leading to a reduced practice effect.

For minimum movement times, there were no significant main effects for device, gain configuration, or session (see Appendix B). The lack of significant variance among minimum movement times was expected as there weren't any configuration manipulations targeting that movement parameter and the effects observed within the mean movement times dissipated. Minimum movement times were products of the larger, closer targets that were easily acquired with each device mechanism regardless of gain configuration or session.

In comparison, maximum movement times were products of smaller, more distant targets that were more difficult to acquire. Multi-gain configurations were developed and implemented to mitigate these excessive times and make it easier to control individual phases of the movement—high gain to quickly get to the target and low gain to accurately acquire it. Therefore, main effects, at least for gain configuration, were most expected for maximum movement times. True to our predictions, there were significant main effects for gain configuration ($F(2, 8) = 10.373$, $p < .05$) and session ($F(1, 4) = 33.099$, $p < .05$) (See Appendix C). The mono-gain configuration yielded the highest maximum movement times ($M = 15.92$, $SD = 9.60$). The dual-gain yielded the second highest ($M = 7.43$, $SD = 2.64$), and the continuous gain yielded the lowest ($M = 6.71$, $SD = 1.82$). Pairwise comparisons did not reveal any significant differences. The dual and continuous gain configurations performed as expected and reduced maximium movement times by nearly half compared to the mono gain configuration. While the continuous gain configuration performed slightly better than the dual gain configuration, it is believed that this difference is due to more of a practice effect than actual variance produced by configuration. Practice effects remained prominent as Session 2 ($M = 9.38$, SD =6.00) yielded significantly better performance than Session 1 ($M = 11.18$. $SD = 7.90$).

There was a significant interaction between device and gain configuration ($F(4, 16) = 3.526$, $P < .05$). When multi-gain configurations were implemented on the joystick and Xbox controller, they had similar effects—more than halving maximum movement times for each respective device. The joystick in the mono gain configuration had a mean maximum movement time of 16.56 seconds. When multi-gain configurations were introduced, these max times decreased to 7.65 seconds with the dual-gain and 6.85

seconds with the continuous gain. The Xbox controller in the mono-gain configuration had a mean maximum movement time of 20.53 seconds, but when multi-gain configurations were introduced, they turned to 5.82 seconds for the dual and 5.87 seconds for the continuous. As for the tablet, its mean maximum movement time with the mono gain configuration was far less to begin with as compared to the other devices (10.67 s). The interaction lies within the application of the multi-gain configurations to the tablet device. These configurations did not nearly have the same effect on the tablet as they did on the joystick and Xbox controller. In fact, application of the dual-gain configuration barely changed the max movement times at all with a mean of 10.61 seconds and the continuous following close behind with a mean of 8.54 seconds. It is believed that the same effects were not observed on the tablet because of the tablet's different operating characteristics. The touchscreen of the tablet enabled the participants to use their finger to adjust cursor position rather than through a mechanical intermediate. The finger acted like a natural gain controller, giving theoretically infinitesimal adjustments without a need for artificial gain configurations. Furthermore, debriefings with participants revealed a different control strategy used specifically with the tablet that involved tapping the screen to nudge the cursor into place. This strategy will be talked about later.

To further verify that it was the high ID targets that were being mitigated by the multi-gain configurations, a oneway ANOVA of movement time for the highest ID targets in each gain configuration was performed (see Appendix E). There was a statistically significant difference between gain configurations ($F(2, 1347) = 81.444$, $P < .05$). Tukey's HSD post hoc test revealed that both the dual-gain ($M = 4743.86$ ms, $SD = 1506.42$) and continuous gain configurations ($M = 4482.58$ ms, $SD = 1276.37$) resulted in significantly faster movement times than the mono-gain configurations (*M* = 6759.68 ms, *SD* = 4673.45) but were not significantly different from one another. These results support the notion that the dual and continuous gain configurations fulfilled their designed purpose by effectively targeting the high ID targets and significantly reducing their movement times. In general, the reduction of maximum movement times caused by high ID targets seems to be the root of significance with the other movement time parameters, mean and minimum, staying relatively the same from configuration to configuration. These results also suggest that there may not be a practical difference between the dual-gain and continuous gain configurations as they were not significantly different from each other. In practice, either configuration would suffice.

The gain usage analysis also helped explain the interaction between device and gain configuration. Unfortunately, due to technical miscommunication, gain histories tied to each target were not acquired as described before, but a history of how the gain flunctuated within each session was acquired. Due to this circumstance, gain histories were analyzed by examining the amount of time spent in each gain value per session per device. Gain histories were examined to determine if the participants were using the gain functionalities and how they were using them. For dual gain, the average amount of time spent in the high and low gains as well as the number of gain switches for each participant, trial, and device were analyzed. Averaged across sessions and subjects, users spent around 12% of the total trial time in the low gain and 88% in the high gain for the Xbox controller and joystick and throttle. For the tablet, a mere .43% of the total trial time was spent in the low gain and 99.6% of the time in the high gain. This bolsters the notion that participants were using the tablet in a different way than the other devices, perhaps using their finger as a means to adjust gain. An average of 158 gain switches occurred with the Xbox controller, 4.5 switches for the tablet, and 138.9 switches for the joystick and throttle. Figure 9 depicts percent time spent in each dual-gain value for each device.

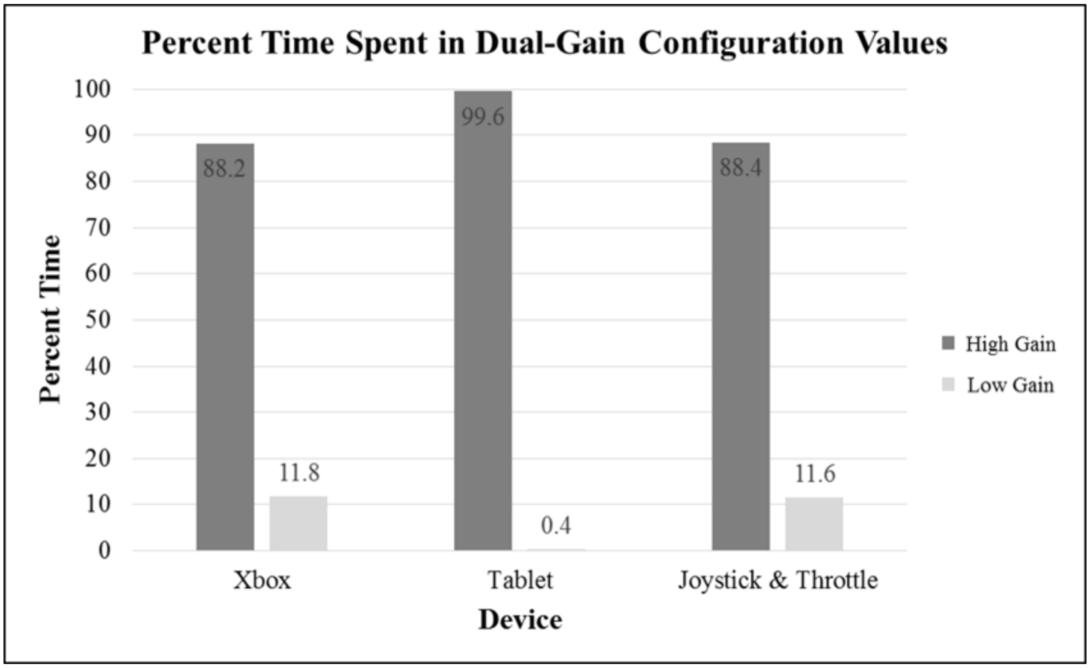


Figure 9. Percentage of time spent in each of the two gain values for each device in the dual-gain configuration.

For the continuous gain configuration, gain values were partitioned into ranges: low, medium, and high. The amount of time spent in each range for each participant, session, and device was calculated. Gain switches were not included in this configuration as it was not feasible to operationalize what constituded as a switch due to the rapid and continuous nature of the gain values. For the Xbox controller, on average, 13.6% of the time was spent in the low gain range, 1.6% in the medium, and 84.9% in the high gain range. For the tablet, 0.1% of the time was spent in the low gain range and 99.9% was spent in the high gain range. For the joystick and throttle, 7.9% of the time was spent in the low gain range, 6.6% in the medum, and 85.5% in the high gain range. Figure 10 depicts percent time spent in each gain range for the continuous gain configuration for each device.

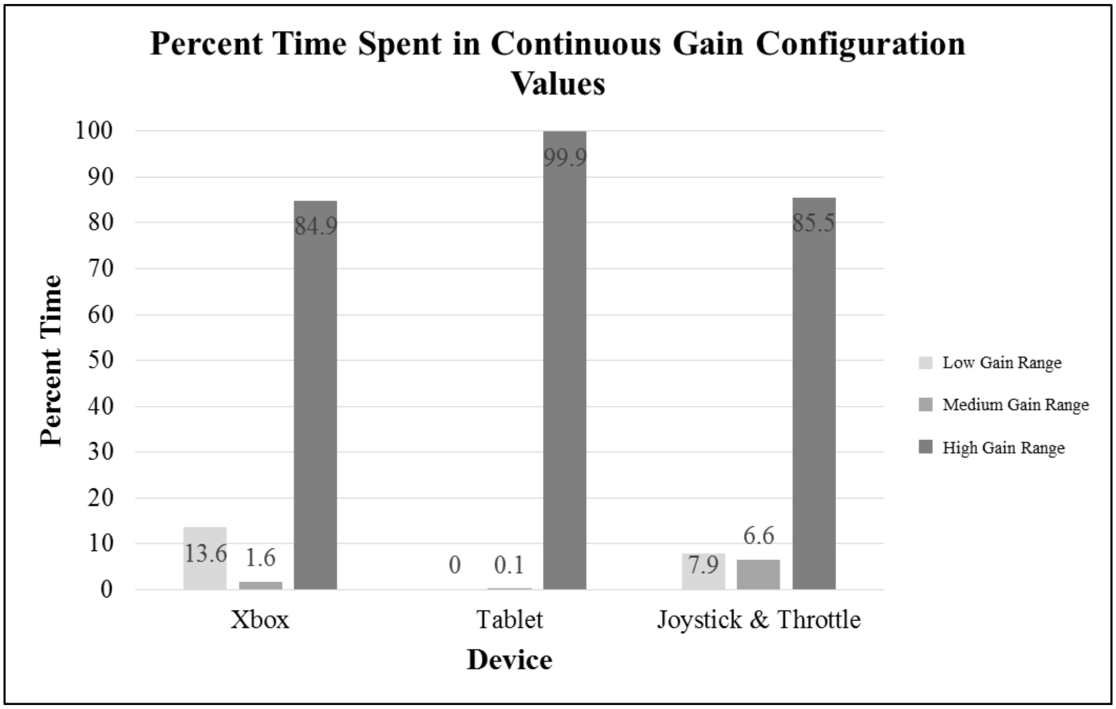


Figure 10. Percentage of time spent in each of the two gain values for each device in the continuous gain configuration.

For the Xbox controller and joystick, gain usage was similar in both the dual and continuous gain configurations. However, for the tablet, alternative gain values were barely, if ever, utilized which helps explain the interaction we see between device and gain configuration. Variance from configuration to configuration was virtually nonexistent. It is possible that participants found the multi-gain configuration implementations on the tablet to be less useful and relied solely on the finger's ability to regulate smaller movements. In fact, informal debriefings of the participants revealed a common control strategy specifically for the tablet. Several of the participants described using a “tapping” method to nudge the cursor into place. To move larger distances, participants would drag their finger across the screen as usual, and when within the vicinity of a target, tended to gently tap on the screen in the direction of the target until the cursor was nudged onto the target. It is believed that this control strategy used across configurations, phased out the usefulness of the multi-gain configurations and led to the observed differences.

Examination of time histories for cursor movements and gain manipulations revealed that participants were using the dual-gain and continuous gain configurations in a different way than designed. For continuous-gain, users were consistently activating the lower gain in a bang-bang control fashion—gains switched abruptly. Instead, of slowly lowering gain and coasting to the target, participants quickly got into the vicinity of the target, lowered the gain abruptly, and made corrective submovements. Figure 11 shows a small portion of gain usage over time for participant 1 using the joystick in a continuous gain configuration. If participants were to use the continuous gain as hypothesized, a smooth continous decrease of gain should have been observed, but instead, a sharp, almost vertical drop off of gain is seen—indicative of the bang-bang style of control. Though we observed decreased movement times with continuous gain and significant differences between dual and continuous configurations in terms of mean movement times, we cannot be certain whether it was caused by the gain configuration itself or merely an artifact of practice considering order was constant. The bang-bang strategy closely alligned with the dual gain configuration and we cannot be certain there’s a difference between the continuous gain configuration and dual gain configuration.

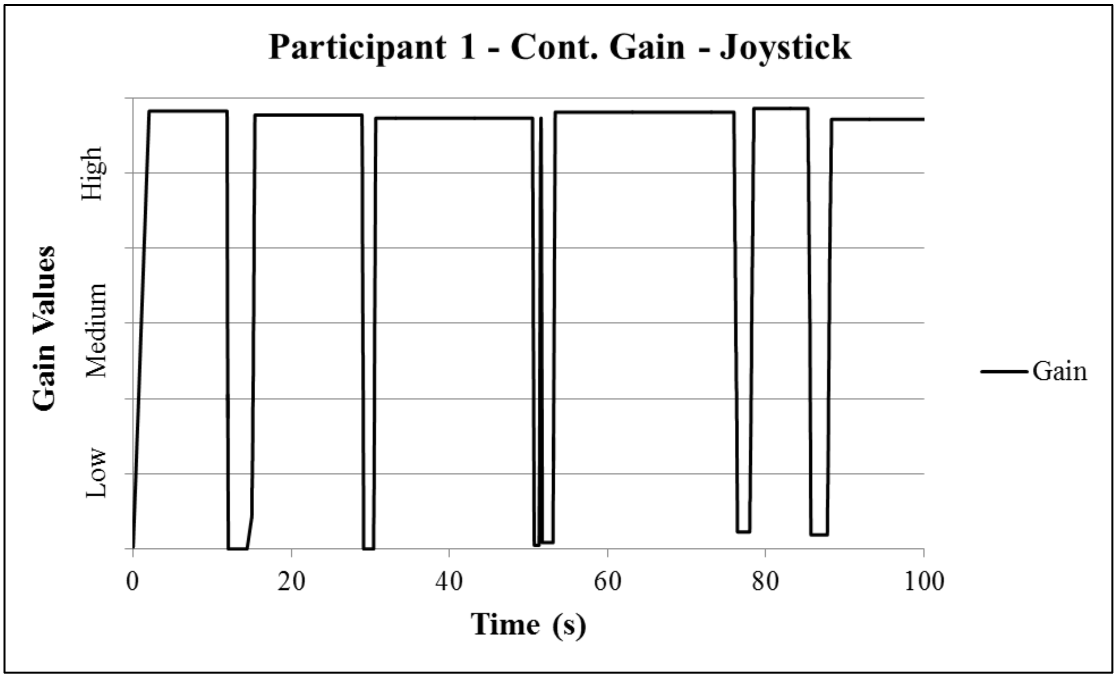


Figure 11. Gain changes over a portion of time for participant 1 using the joystick & throttle in a continuous gain configuration.

There was also a significant interaction between gain configuration and session ($F(2, 8) = 6.336$, $p < .05$) for maximum movement times. The mono-gain and dual-gain configurations saw similar improvement from session 1 to 2. The mono-gain configuration went from a mean of 17.91 seconds in session 1 to 13.93 seconds in session 2. The dual-gain configuration went from a mean of 8.86 seconds in session 1 to 7.19 seconds in session 2. The continuous gain configuration performance stayed virtually flat with a mean of 7.15 seconds in session 1 and 7.02 seconds in session 2. The flatlining in the continuous gain configuration is thought to be attributed to practice considering that it was the last configuration to be tested and the design was not counterbalanced.

For information-processing rates, there were significant main effects for gain configuration ($F(2, 8) = 10.373$, $p < .05$) and session ($F(1, 4) = 33.099$, $p < .05$) (See

Appendix D). The dual-gain configuration (M = 2.48 bits/s) yielded lower rates than the mono-gain configuration (M = 1.78 bits/s). The continuous gain configuration (M = 2.78 bits/s) yielded the lowest rates. Pairwise comparisons did not yield any significant differences amongst gain configurations. However, session 2 (M = 2.32 bits/s) yielded significantly better performance than session 1 (M = 2.15 bits/s). A main effect for gain configuration was expected as the addition of alternative gains made the task easier—enabling the user to process a greater number of bits. A practice effect going from session 1 to session 2 was also expected.

There was also a significant interaction between device and gain configuration ($F(4, 16) = 3.526$, $p < .05$) as well as gain configuration and session ($F(2, 8) = 6.336$, $p < .05$). Figure 12 depicts the mean information-processing rates (bits/s) across participants for device, configuration, and session. Interpretation of the interaction between device and gain configuration, once again, revolves around the effect of the gain configurations on the tablet device. While the joystick and Xbox controller saw increased IP rates in the multi-gain configurations, the tablet yielded much flatter, stabilized IP rates across gain configurations which again, is attributed to different operating characteristics and exclusive control strategy. As for the interaction between gain configuration and session, the continuous gain configuration saw less improvement across sessions with a difference of .13 seconds compared to the mono and dual-gain configurations with .20 and .19 second differences, respectively. This difference is attributed to the continuous gain configuration being administered last in the experiment and the design being unbalanced.

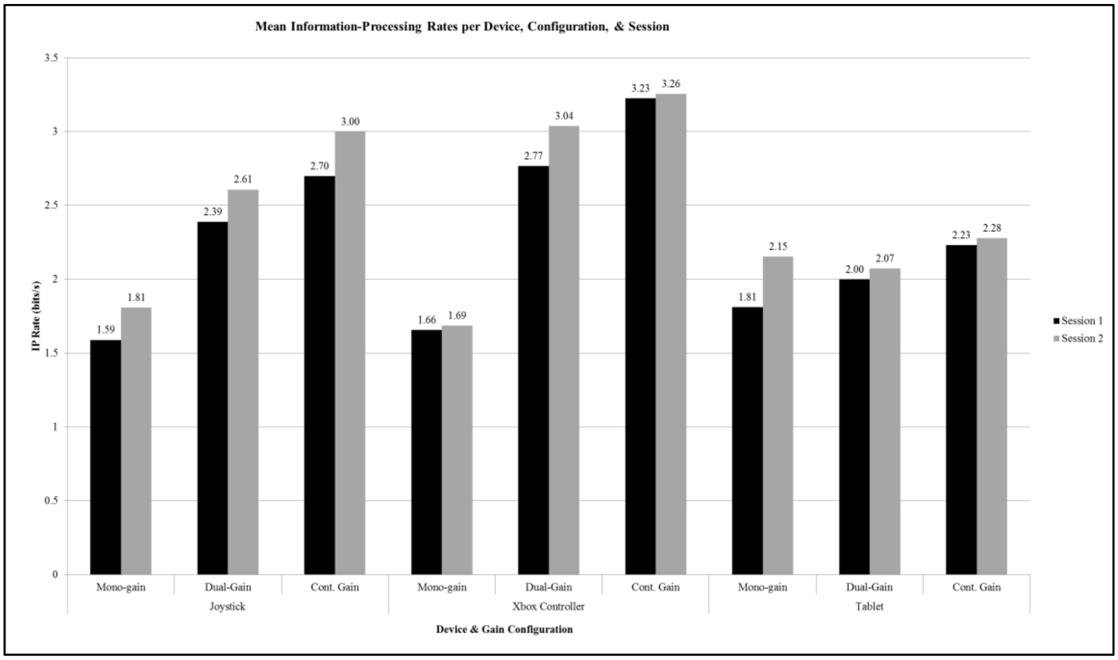


Figure 12. Mean information-processing rates (bits/s) across participants for device, configuration, and session.

Lastly, in terms of model fit, Table 2 depicts R^2 values for each participant for each session with every device/gain configuration combination. For unfiltered raw data, acceptable R^2 values were achieved. On average across sessions, better fits were achieved with the dual-gain and continuous gain configurations. Deviations from linearity were observed in the mono-gain conditions. It is suspected that due to high movement time costs in the high ID conditions caused by an instable gain.

Table 2

R Squared Values

	Joystick						Xbox Controller						Tablet					
	Mono-Gain		Dual-Gain		Cont. Gain		Mono-Gain		Dual-Gain		Cont. Gain		Mono-Gain		Dual-Gain		Cont. Gain	
Participant	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
1	0.31	0.51	0.51	0.56	0.53	0.52	0.47	0.45	0.59	0.63	0.60	0.60	0.38	0.42	0.41	0.45	0.39	0.39
2	0.20	0.23	0.43	0.44	0.44	0.43	0.25	0.26	0.53	0.52	0.52	0.50	0.44	0.38	0.35	0.43	0.39	0.49
3	0.24	0.29	0.41	0.47	0.49	0.47	0.15	0.17	0.53	0.53	0.35	0.42	0.32	0.32	0.33	0.38	0.39	0.39
4	0.32	0.42	0.51	0.52	0.54	0.51	0.42	0.50	0.63	0.58	0.60	0.61	0.46	0.48	0.55	0.47	0.51	0.52
5	0.27	0.42	0.56	0.51	0.56	0.50	0.30	0.32	0.44	0.61	0.58	0.58	0.36	0.36	0.39	0.47	0.45	0.47
Average	0.32		0.49		0.50		0.33		0.56		0.54		0.39		0.42		0.44	

Note. Values are based on regression of movement times with index of difficulty. Averages are calculated across trials for each session for each device/gain configuration combination.

Table 3 depicts Y-intercept values for each participant for each session with every device/gain configuration combination. On average across sessions, Y-intercepts in the dual-gain and continuous gain configurations were higher than the mono-gain configuration.

Table 3

Y-Intercept Values

	Joystick						Xbox Controller						Tablet					
	Mono-Gain		Dual-Gain		Cont. Gain		Mono-Gain		Dual-Gain		Cont. Gain		Mono-Gain		Dual-Gain		Cont. Gain	
Participant	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
1	1.13	0.77	0.86	0.72	0.79	0.88	0.61	0.99	0.83	0.81	0.81	0.82	1.48	1.47	1.29	1.26	0.81	0.82
2	-0.17	0.19	0.73	0.88	0.80	1.00	-0.41	-0.20	0.90	0.90	0.94	1.01	1.11	1.39	1.40	1.41	0.94	1.01
3	0.32	0.44	0.77	0.75	0.73	0.89	0.15	0.26	0.77	0.84	1.18	0.92	1.25	1.54	1.39	1.26	1.18	0.92
4	0.59	0.60	0.95	0.78	0.90	0.99	0.40	0.65	0.87	0.81	0.81	0.80	1.18	1.20	1.18	1.31	0.81	0.80
5	0.95	0.83	0.82	0.80	1.01	0.92	0.13	0.34	0.81	0.84	0.95	0.96	1.43	1.25	1.12	1.14	0.95	0.96
Average	0.57		0.81		0.89		0.29		0.84		0.92		1.33		1.27		0.92	

Note. Values are based on regression of movement times (s) with index of difficulty (bits). Averages are calculated across trials for each session for each device/gain configuration combination.

4. DISCUSSION

In general, findings supported our hypotheses. Multi-gain configurations designed to mitigate excessive movement times yielded significantly lower maximum movement times as well as significantly lower mean movement times and information-processing rates than the mono-gain configuration. The continuous gain configuration, as predicted, performed the best, but by very little compared to the dual-gain configuration. It's unclear whether this difference was a result of practice or configural differences. Furthermore, an analysis of gain usage revealed that participants used the continuous gain configuration in the same way as the dual-gain configuration, thus reinforcing the argument for a practice effect.

Because of the sharp decreases in maximum movement times observed in the multi-gain configurations, we persist in that large max times in the mono-gain conditions were a result of excessive oscillation around the smaller targets due to a gain set too high for stability constraints. Under the multi-gain configurations, it is inferred that these oscillations disappeared and thus reduced times. The lack of significant variance within the minimum movement times across device and gain configuration bolsters this argument. It didn't matter what device or configuration was used as each was sufficient enough to acquire the larger, closer targets. The difference came out in the smaller targets that took longer to capture in the mono-gain configuration but were successfully mitigated by the dual and continuous gain implementations that offered lower gain values. Secondary lower gain values added a level of precision in the closed-loop feedback component that diminished oscillations and reduced maximum movement times. Although a spatial or target based gain analysis wasn't possible, an analysis of gain usage indicated that participants were using the lower gains, but only for certain devices. Unfortunately, due to technical miscommunication, we were unable to match individual gain manipulations to particular targets, but we predict that participants activated the lower gain when acquiring smaller targets as hypothesized. Talking with participants supported this notion.

The success of the multi-gain configurations was dependent on device characteristics as evidenced in the interactions between device and gain configuration. The tablet did not perform as well as the Xbox controller and joystick due to its input differences. It seems that the touch mode of input was not as receptive to gain manipulation as the more physical trigger or throttle present in the other devices. Participants informed us that it was difficult to manipulate gain on the tablet while also trying to acquire targets on the same surface. Depressing the trigger on the Xbox controller or moving the throttle were easier mechanisms as they were separate from cursor movement mechanisms. Results revealed that the Xbox controller performed the best of all devices within the multi-gain configurations, thus it is believed the mechanical characteristics of the Xbox controller were best suited for the gain configurations implemented. Compared to the throttle, the trigger was much easier and faster to operate. Users simply could switch back and forth between gains with a single finger where, with the throttle, switching between gains required a large gross movement that consumed more time.

Cursor navigation was also dependent on device as already pointed out with the "tapping" strategy used with the tablet. Using the tablet, it was difficult to maintain continuous cursor movement onto the target. Therefore, a tapping strategy evolved that got the cursor closer to a continuous nature. While this strategy proved useful in some regard as it was better than the mono-gain configurations on the Xbox and joystick, it was not as good as the other devices with the multi-gain configurations. The Xbox controller and joystick had similar mechanisms in regard to cursor movement. The Xbox provided a small thumbstick for cursor navigation while the joystick provided a larger joystick version. We hypothesize that another reason the Xbox outperformed the joystick was because it was easier to and less time-consuming to operate the small thumbstick than the larger joystick that required larger gross movements of the wrist. In conclusion, it seems that mode of input (touch vs. mechanical) as well as the displacement distance a limb had to move played a role in how well the device performed in regards to gain manipulation and target acquisition. As a takeaway, developers seeking to implement multi-gain control should use a mechanical device with separate easy-to-use control mechanisms for cursor movement and gain manipulation. However, further experimentation with the touch mode of input is needed to determine its usefulness.

There was significant performance improvement observed from session to session for each participant. It is believed that this improvement was a residual of the practice effect as the 10 acquisition trials before each session did not provide enough practice to normalize performance. This notion is supported by the literature as it suggests participants can anticipate and develop a central representation of the pattern of muscle activation needed to acquire the targets—getting closer to the target without overshooting it leading to a decrease of secondary corrective submovements. It is believed that this sort of process occurred as the participants gained experience acquiring targets with each device. Unfortunately, a huge limitation of the study, especially in light of the literature, was that the design was not completely counterbalanced due to time limitations and previously existing data. Therefore, some of the variance in performance could be due to the discussed practice effect and developed central representation.

The miscommunication leading to a lack of target-specific gain data was another shortcoming. Had this been achieved, more definitive conclusions regarding the size of targets and corresponding gain usage could be drawn. That is, acquisition of smaller targets would tend to be carried out with smaller gain values as they afforded more precise submovements. Instead, we are left with the differences in mean and max movement times and IP rates as evidence for this phenomenon.

The findings in this study have a couple of implications and takeaways. For one, any system that involves target acquisition needs to pay close attention to the setting of gain values as well as consider implementing multi-gain configurations to improve performance as evidenced in this study. Systems in which users have to navigate over large distances and acquire smaller targets would vastly benefit. Furthermore, multi-gain control offers a less intrusive alternative to the previously discussed target acquisition enhancements and involuntary gain manipulations that tend to distort the workspace and targets and interfere with the operator. However, multi-gain control logic seems to be limited by device characteristics such as method of input. Future studies should more closely examine and measure gain changes over time for multiple multi-gain configurations. In this way, control strategies across different configurations will become more apparent. Secondly, the same experiment could be repeated with target-specific gain data to ensure that lower gains were being used to acquire smaller targets.

In conclusion, based on preliminary observations of insufficient performance using devices with a single gain, configurations involving multiple gain values triggered at the discretion of the user were implemented. The multi-gain configurations, particularly access to lower gain values, were hypothesized to mitigate excessive oscillations in the secondary movement phase when trying to select smaller targets. Although unable to spatiotemporally record cursor movements and gain changes as a function of target size, results indicated that the dual and continuous gain configurations yielded significantly lower movement times and IP rates than the mono-gain configuration. Gain usage analyses showed that participants were using the configurations 12-14% of the time but only for the Xbox controller and joystick/throttle. The gain configurations on the tablet were used less than 1% of the time. As discussed, this is believed to be a result of the 'touch' mode of input for the tablet as compared to the mechanical inputs of the Xbox controller and joystick. The results achieved in this study are likely to hold up, but they do come with some implications. Unfortunately, the study was not counterbalanced and practice effects were likely to have played a role. Regardless, the implementation of multi-gain configurations resulted in faster and more efficient performance while be it device dependent. Future research should implement clearer metrics for measuring gain manipulations and cursor movement over time as well as the dependence on device characteristics.

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APPENDIX A

MEAN MOVEMENT TIME ANOVA

Table A1

Within-Subjects Repeated Measures ANOVA for Mean Movement Times

Source	SS	df	MS	F	p-value
Device	14160000	2	7080257	25.95*	0.00
Gain Configuration	7107805	2	3553903	13.20*	0.00
Session	587210.2	1	587210.2	676.55*	0.00
Device*Gain Configuration	1038197	4	259549.3	2.06	0.13
Device*Session	157867.2	2	78933.59	8.62*	0.01
Gain Configuration*Session	72533.72	2	36266.86	2.94	0.11
Device*Gain Configuration*Session	176038.8	4	44009.69	0.98	0.45

Note. *p < .05

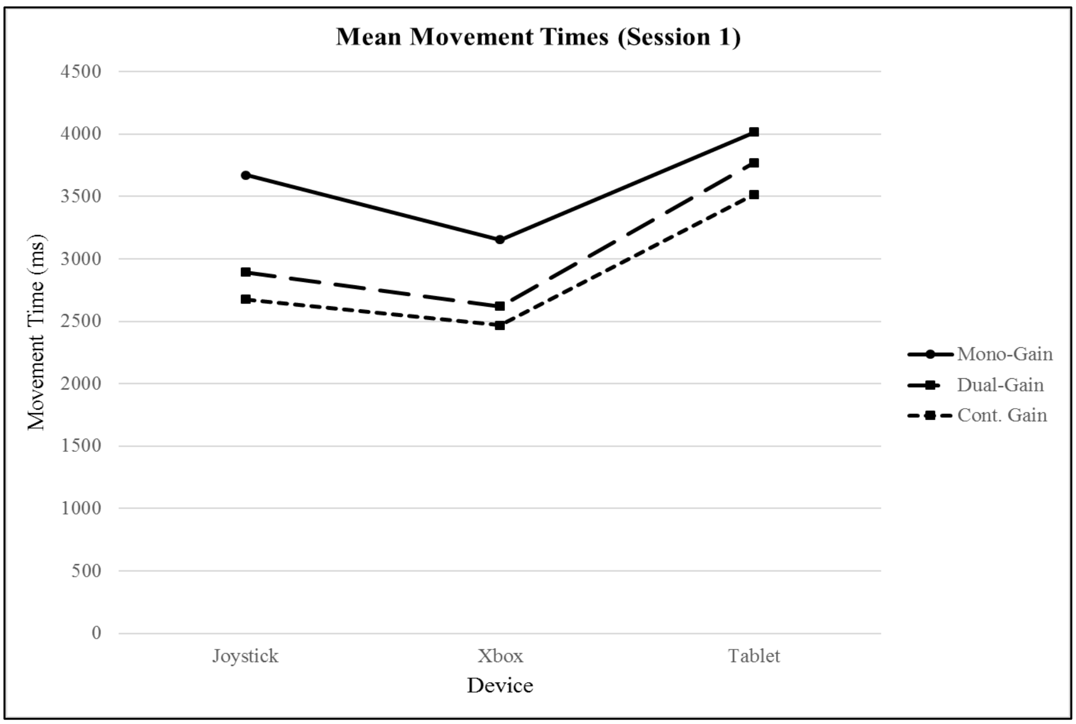

Figure A1. Mean movement times for each device and gain configuration in Session 1.

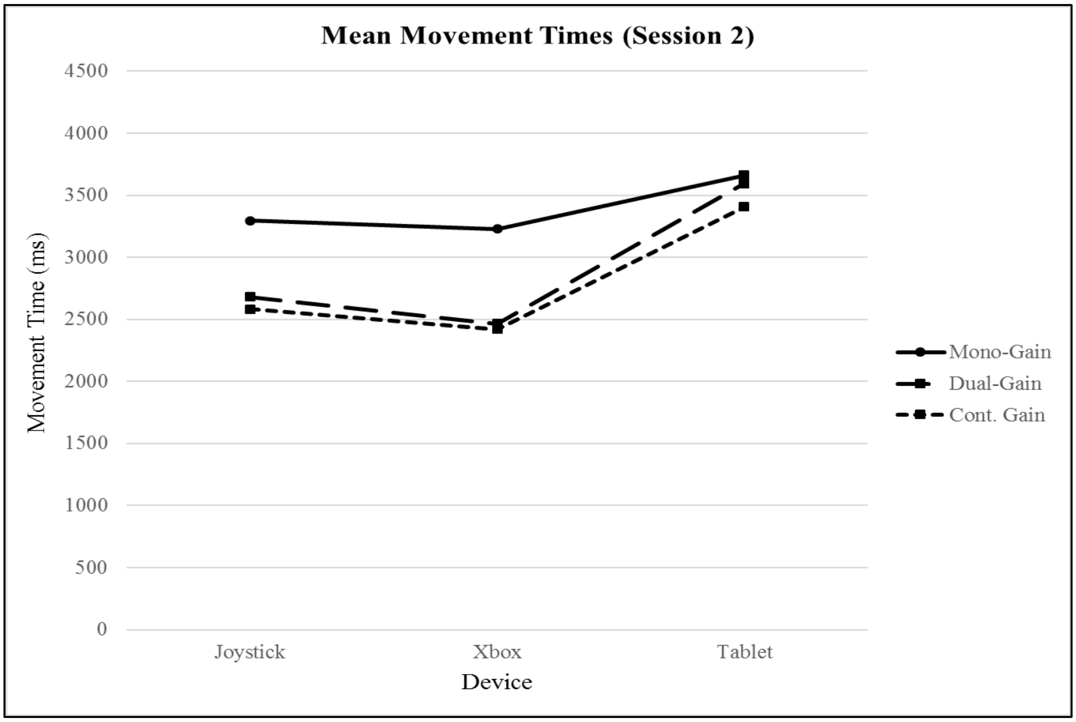

Figure 2A. Mean movement times for each device and gain configuration in Session 2.

APPENDIX B

MINIMUM MOVEMENT TIME ANOVA

Table B1

Within-Subjects Repeated Measures ANOVA for Mean Minimum Movement Times

Source	SS	df	MS	F	p-value
Device	287742.5	2	143871.3	4.12	0.06
Gain Configuration	7590.473	2	3795.236	0.15	0.86
Session	11759.41	1	11759.41	1.14	0.35
Device*Gain Configuration	19399.92	4	4849.981	0.22	0.92
Device*Session	116672.8	2	58336.41	3.09	0.10
Gain Configuration*Session	84103.76	2	42051.88	1.93	0.21
Device*Gain Configuration*Session	219614.4	4	54903.6	4.81*	0.01

Note. *p < .05

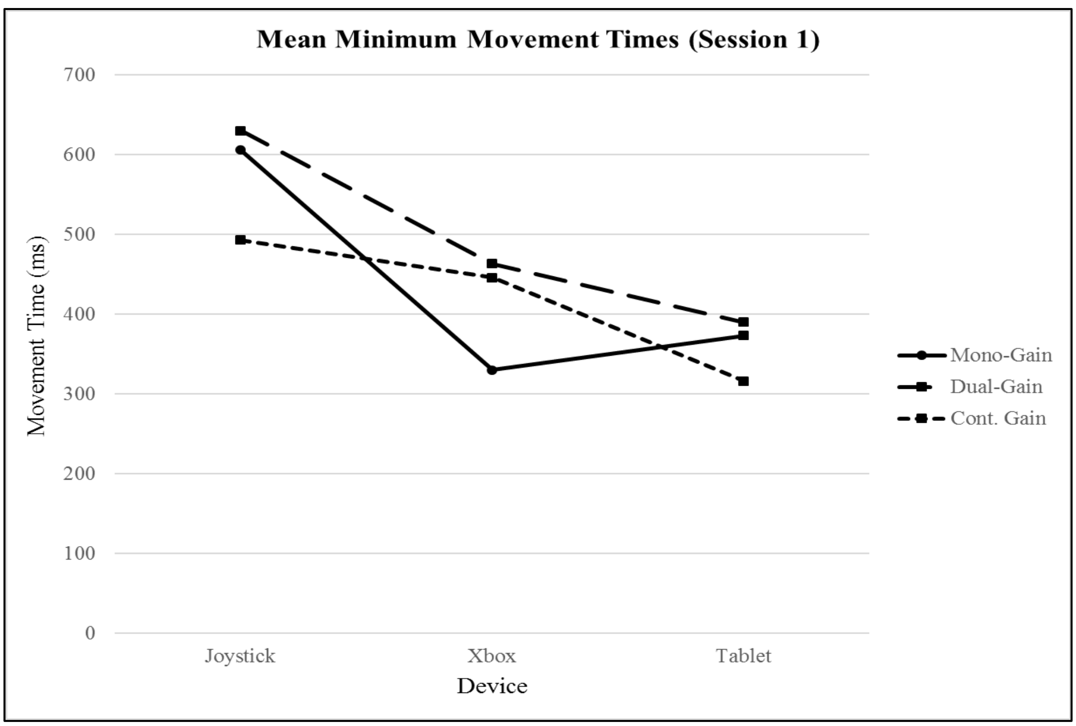

Figure 1B. Mean minimum movement times for each device and gain configuration in Session 1.

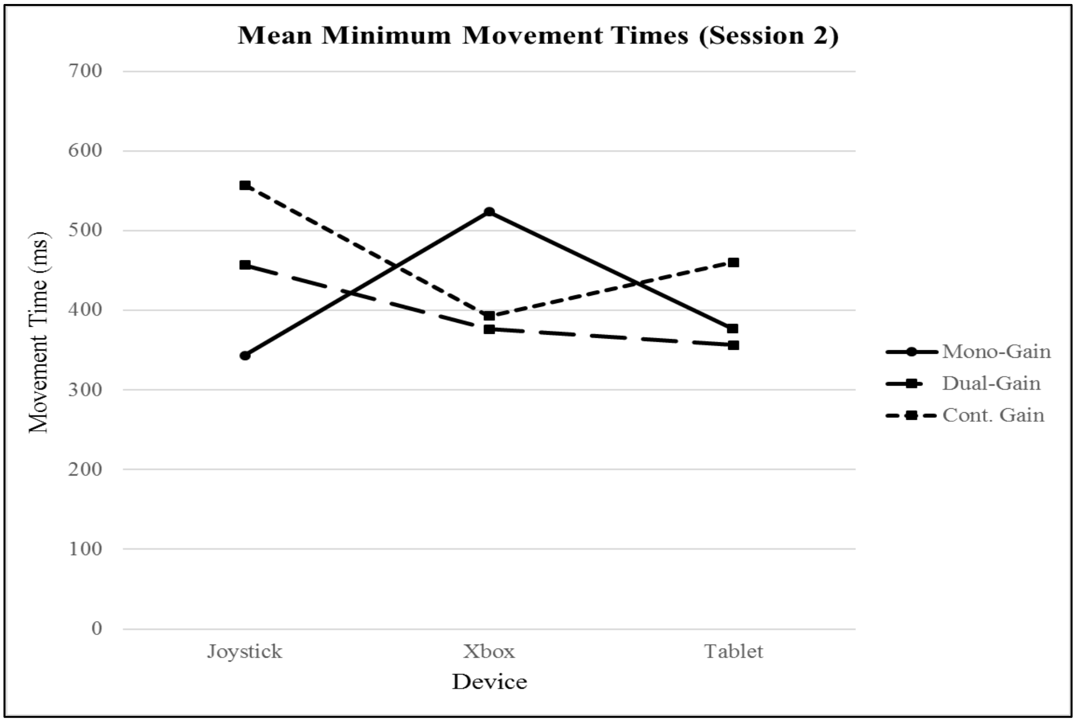

Figure 2B. Mean minimum movement times for each device and gain configuration for Session 2.

APPENDIX C

MAXIMUM MOVEMENT TIME ANOVA

Table C1

Within-Subjects Repeated Measures ANOVA for Mean Maximum Movement Times

Source	SS	df	MS	F	p-value
Device	52280000	2	26140000	0.80	0.48
Gain Configuration	1.57E+09	2	7.87E+08	10.37*	0.01
Session	75420000	1	75420000	33.01*	0.01
Device*Gain Configuration	4.98E+08	4	1.25E+08	3.53*	0.03
Device*Session	1112719	2	556359.4	0.35	0.71
Gain Configuration*Session	56340000	2	28170000	6.34*	0.02
Device*Gain Configuration*Session	13510000	4	3378717	1.65	0.21

Note. *p < .05

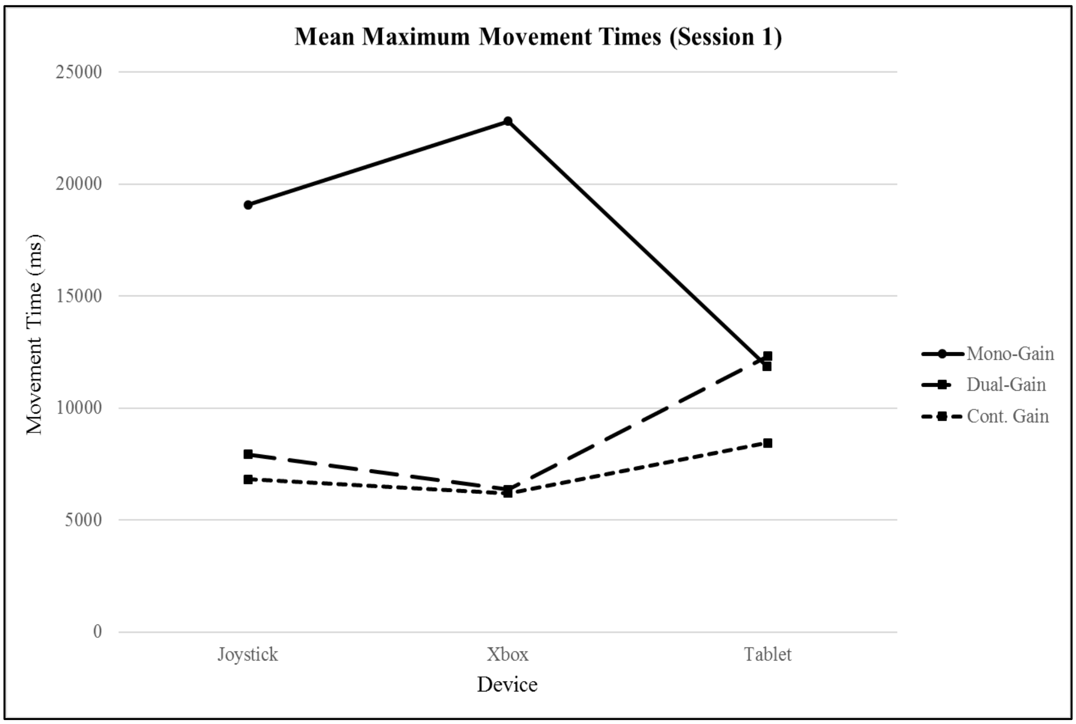

Figure C1. Mean maximum movement times for each device and gain configuration for Session 1.

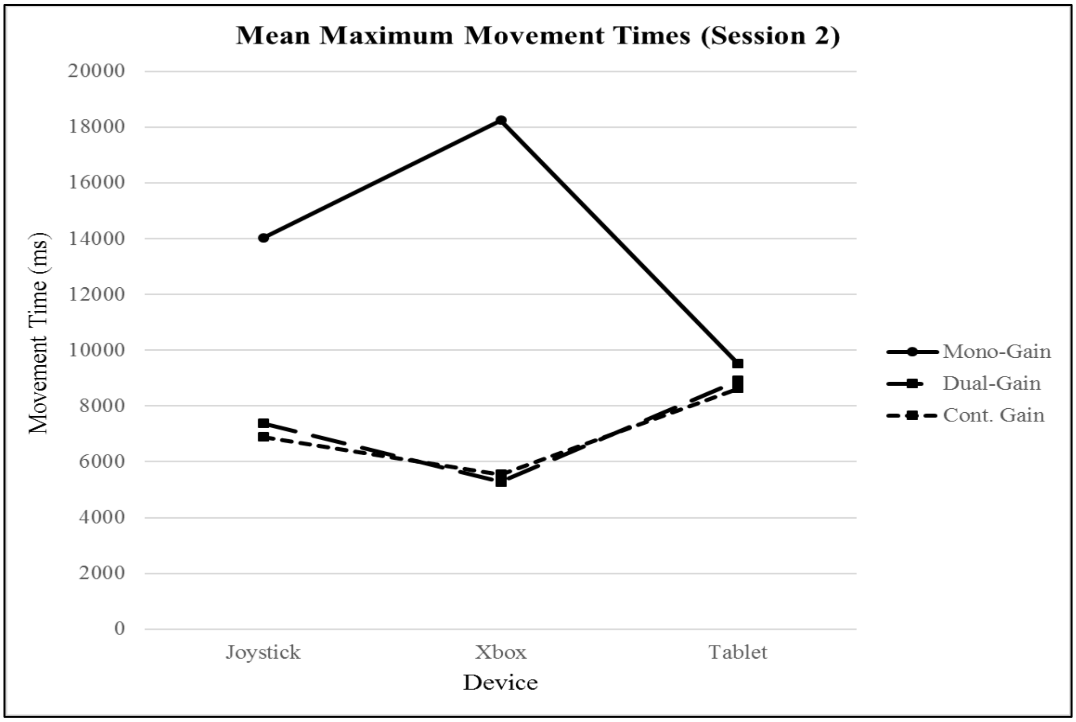

Figure C2. Mean maximum movement times for each device and gain configuration for Session 2.

APPENDIX D

INFORMATION-PROCESSING RATES ANOVA

Table D1

Within-Subjects Repeated Measures ANOVA for Mean IP Rates

Source	SS	df	MS	F	p-value
Device	52280000	2	26140000	0.798	0.483
Gain Configuration	1.57E+09	2	7.87E+08	10.373*	0.006
Session	75420000	1	75420000	33.099*	0.005
Device*Gain Configuration	4.98E+08	4	1.25E+08	3.526*	0.03
Device*Session	1112719	2	556359.4	0.354	0.712
Gain Configuration*Session	56340000	2	28170000	6.336*	0.022
Device*Gain Configuration*Session	13510000	4	3378717	1.652	0.21

Note. *p < .05

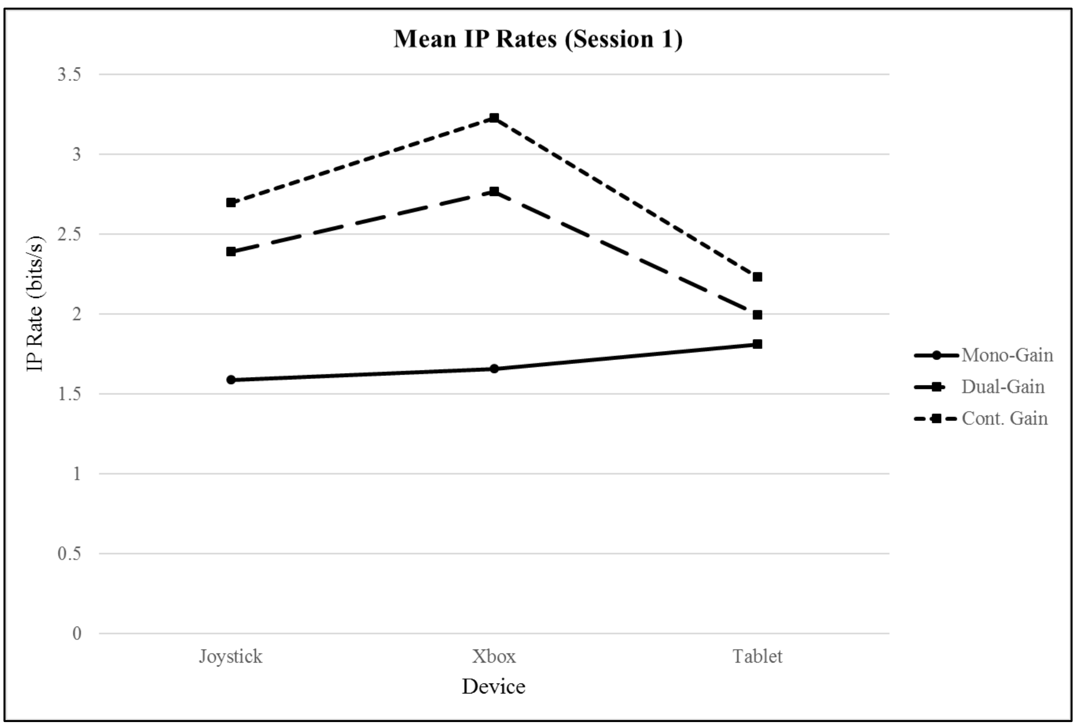

Figure D1. Mean information-processing rates for each device and gain configuration for Session 1.

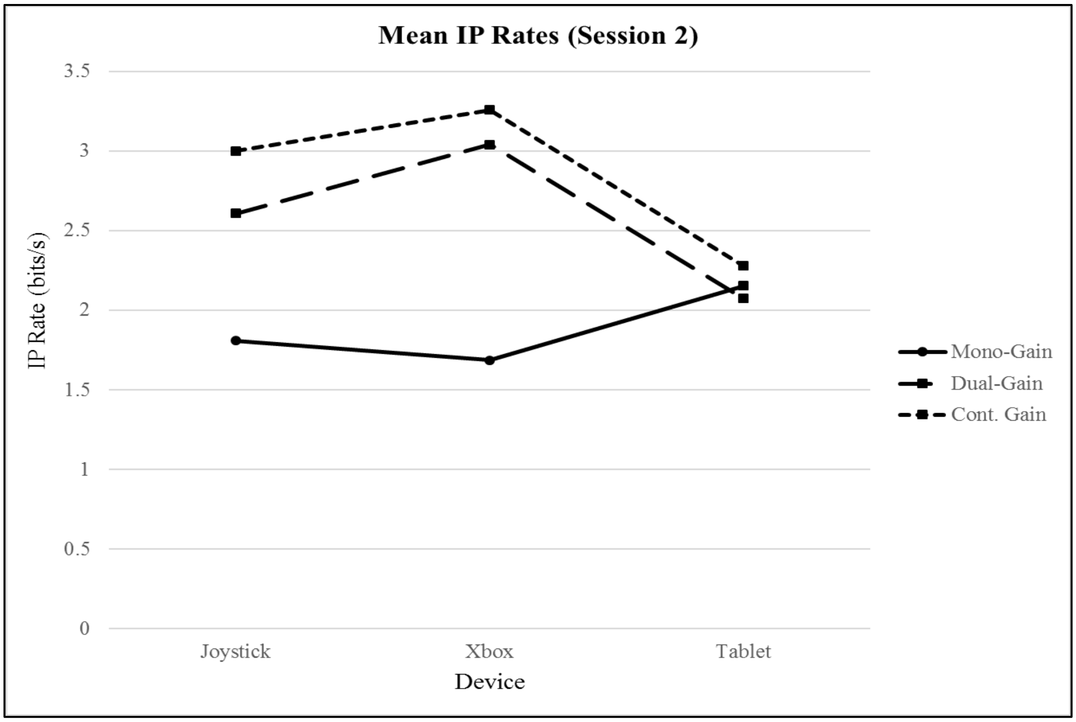

Figure D2. Mean information-processing rates for each device and gain configuration for Session 2.

APPENDIX E

HIGHEST ID TARGETS ANOVA

Table E1

Oneway ANOVA of Movement Time for High ID Targets in each Gain Configuration

Source	SS	df	MS	F	p-value
Between Groups	1.40E+09	2	6.99E+08	81.444*	0.000
Within Groups	1.16E+10	1347	8579852		
Total	1.30E+10	1349			

Note. *p < .05

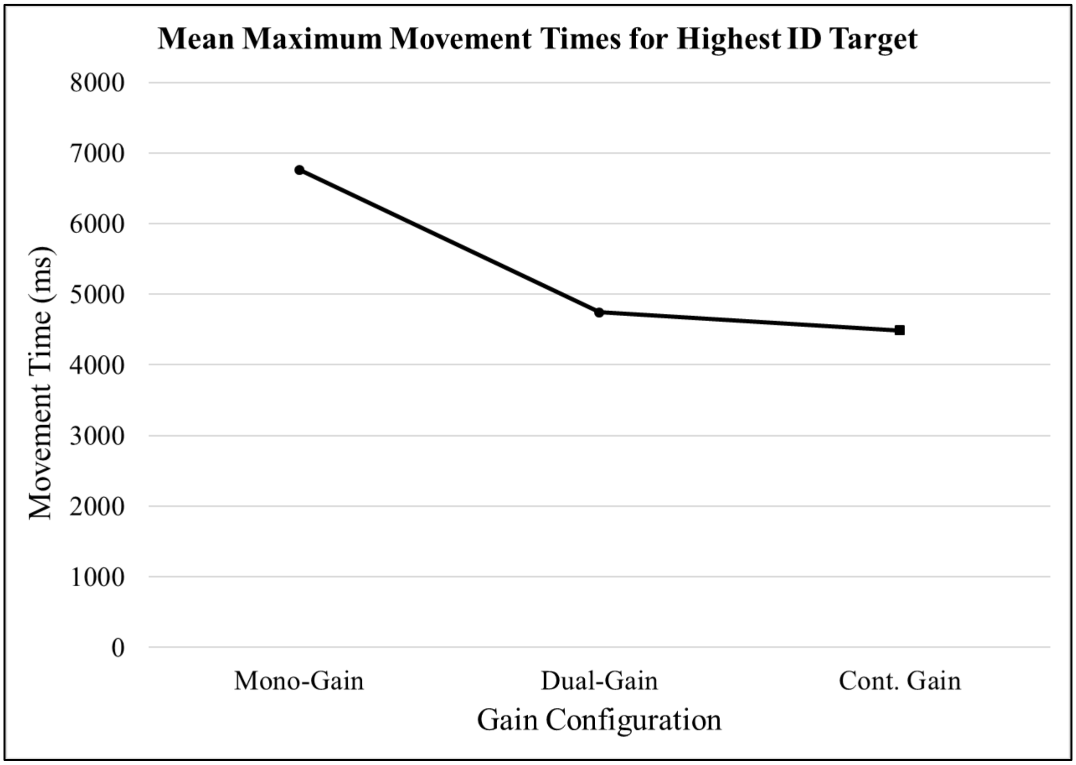

Figure E1. Mean maximum movement times for highest ID targets for each gain configurations.