Cleveland State University
EngagedScholarship@CSU

ETD Archive

2016

Variability and Location of Movement Endpoint Distributions: The Influence of Instructions for Movement Speed and Accuracy

Abhishek Dey

VARIABILITY AND LOCATION OF MOVEMENT ENDPOINT DISTRIBUTIONS: THE INFLUENCE OF INSTRUCTIONS FOR MOVEMENT SPEED AND ACCURACY

ABHISHEK DEY

Bachelor of Science in Psychology

Northeastern University

January 2011

submitted in partial fulfillment of the requirements for the degree

MASTER OF ARTS IN PSYCHOLOGY

at

CLEVELAND STATE UNIVERSITY

May 2016

We hereby approve this thesis for

Abhishek Dey

Candidate for the Master of Arts in Psychology degree for the

Department of Psychology

and the CLEVELAND STATE UNIVERSITY

College of Graduate Studies

Thesis Chairperson, Dr. Andrew B. Slifkin

Department & Date

Thesis Committee Member, Dr. Conor T. M^{c}Lennan

Department & Date

Thesis Committee Member, Dr. Albert F. Smith

Department & Date

Thesis Committee Member, Dr. Kenneth E. Vail

Department & Date

Student's Date of Defense: April 27th, 2016

ACKNOWLEDGEMENTS

With all my being, I would like to thank my parents, for giving me the opportunity to explore and muddle through life as I searched for my passion. Without the precarious balance they maintained of both pushing me to do my best, and also leaving me to my own devices, I would not have been able to accomplish all the things I have so far.

I would like to also thank my closest friend, Amy Palinski, for believing in me when I did not, for making me laugh when I needed to, and for pushing me to strive for more than I probably deserve. Your friendship means the world to me and I am lucky to have been able to meet you.

Finally, I thank my advisor, Dr. Andrew Slifkin, for his patience, advice, respect, and guidance. Dr. Slifkin exemplifies all that is most desirable in a mentor and I am grateful to have been his student.

VARIABILITY AND LOCATION OF MOVEMENT ENDPOINT DISTRIBUTIONS: THE INFLUENCE OF INSTRUCTIONS FOR MOVEMENT SPEED AND ACCURACY

ABHISHEK DEY

ABSTRACT

An influential theory of motor control predicts that targeted hand movements should be aimed at the target center and that the variability of movement endpoint distributions should fill the target region (Meyer et al., 1988). Because increases in the amount of movement endpoint variability correlates with increases in movement speed (Schmidt et al., 1979), centering the distribution on the target center and expanding variability to the limits of the target boundaries should allow for maximization of movement speed, without the production of movement errors (i.e., target misses). Slifkin and Eder (2016) recently found that those predictions only held over a range of small target widths; however, as target width increased the endpoint distribution variability increasingly underestimated the variability permitted by the target boundaries and the location of the distribution center increasingly underestimated the target center. There was a strong relationship observed between the unutilized target region and aim points shifting away from the target center. Those results suggest that the downward shift in endpoint distribution location was based on "knowledge" of the amount of endpoint variability relative to the unused space in the target, and such downward shifts may reflect a reduction of travel costs (e.g., movement distance). Thus, there is a possibility that there is a link between unused space and how much distance minimization occurs. Here, we extend the results of Slifkin and Eder (2016) by explicitly manipulating endpoint distribution variability through a manipulation of task instructions, thereby allowing a more direct investigation of the link between unused space and distance minimization. The instructions emphasized either 1) movement accuracy, 2) both movement accuracy and speed, or 3) movement speed. Participants generated movements under different target width and amplitude requirement conditions. Variability increased as the emphasis on movement speed increased. In turn, as variability increased within a given target width condition, the amount of unused space within the target region decreased. The results provide support for the notion that the relation between aiming and knowledge of variability was maintained, but the nature of the relationship was influenced by the instruction conditions. The implications of these results on models of optimal motor control will be discussed.

Keywords: motor control, aiming, movement variability, target width, target utilization, constant error

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

Even the simplest of actions we perform to interact with our environment are riddled with stochastic uncertainty. Such uncertainty can arise from variations in the perceptual qualities of stimuli and from internal noise generated by our motor systems (Adam, 1992; Beers, 2009; Churchland, Afshar, & Shenoy, 2006). Nevertheless, in goal-oriented tasks, we are able to make movements with a good degree of precision and success, taking into account noise and uncertainty. For instance, when a pianist plays an arpeggio, he or she needs to be able to make spatially and temporally precise finger movements with their fingers. Each finger movement requires the activation of the appropriate motor neurons and muscles with a specific amount of force. Activation of motor neurons and muscles are inherently stochastic in nature. The melody created by the pianist is thus dependent on a symphony generated by his or her motor system, which is intrinsically noisy. In the literature, it has been argued that individuals pick optimal, or near-optimal, strategies in making movements such that they take account of variability inherent within the task and the motor system (e.g., Elliott, Hansen, & Grierson, 2009; Gepshtein, Seydell, & Trommershauser, 2007; Seydell, Mccann, Trommershauser, & Knill, 2008; Todorov & Jordan, 2002; Trommershäuser, Landy, & Maloney, 2003). However, it remains unclear as to how this optimization is being achieved in goal-oriented tasks.

Fitts' (1954) classic experiment investigated arm movements using a reciprocal aiming tasks in which participants had to move back and forth between two rectangular target plates without touching the error regions around the targets. The width and distance between the targets were varied and performance was closely related to an index of difficulty that was formalized as: $\log_2(\frac{2A}{W})$. According to Meyer et al. (1988), and the stochastic optimized submovement model, for Fitts' tasks, planned movements should be aimed at the center of targets to maximize speed and accuracy. When participants increase the range of the distribution of their movement endpoints it indicates that their movements are less accurate.[1] According to the speed-accuracy tradeoff, accuracy is inversely related to speed, such that lower accuracy, or increased movement variability, will be positively correlated with increases in movement speed (Elliott, Hansen, Grierson, Lyons, Bennett, & Hayes, 2010; Fitts, 1954; MacKenzie, 1991; Meyer et al, 1988; Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979; Woodworth, 1899). The faster participants move, the more spread out their endpoints should be. Consequently, Meyer et al. (1988) concluded that participants should, ideally, calibrate their accuracy such that the spread of their movement endpoints should encompass the entirety of the width of the

[1] The term accuracy, used in this context, is not a measure of how often participants "hit" the target, but rather, reflects the magnitude of movement variability. That is, in the current context, accuracy is more concerned with the level of movement endpoint consistency rather than the number or proportion of hits-to-misses.

target. Further, the model assumes their distribution of movement endpoints is normal, and as such, participants should aim at the center of the target. Aiming at the center of the target when movement endpoints encompass the entirety of the width of the target is needed to minimize target misses.

In many aiming tasks, the use of small targets constrain movement variability. That is, movement endpoint variability is limited by the goal to remain within the boundaries of the target. At those small target widths, participants' endpoint variability encompasses the whole target and task specified width is equivalent to movement variability. However, does this remain true when target widths increase in size? Zhai, Kong, and Ren (2004) examined movement endpoint variability at different target widths by taking the ratio of 96% of the range of the distribution of movement endpoints, defined as effective target width (W_E) and target width (W) specified by the task. These researchers defined this ratio as *target utilization,* or in other words, the proportion of the target width used by individuals. The results of Zhai et al. (2004) indicate that target utilization was dependent on both amplitude requirement (distance between the centers of the targets) and W, but W had a much more robust effect on utilization, such that as W increased, target utilization decreased. Those results are in contradiction with predictions made by the stochastic optimized submovement model. Certain questions then need to be answered based on the observed results, namely, (1) why do participants not utilize the entire width of the target, and (2) if the distribution of endpoints does not encompass the entire target, where is the distribution centered within the target?

Slifkin and Eder (2016) investigated those questions by examining the influence of W and movement amplitude requirement on both the W_E, and the mean of the distribution of movement endpoints. These researchers utilized five Ws (i.e., 5, 10, 20, 40, 80 mm) and three amplitude requirements (80, 160, 320 mm) and instructed participants to move as quickly and as accurately as possible, balancing both speed and accuracy; such instructions are typical in studies on manual aiming. The authors defined the difference in distance between the mean location of the distribution and the center of the target as constant error (CE). Thus, negative and positive CE values reflect under- and over-shooting of the center of the target, respectively. When CE is equal to zero, the mean location of the distribution is at the center of the target. The results of Slifkin and Eder (2016) indicate that at smaller W conditions (5 and 10 mm) the stochastic optimized submovement model was supported. Under those conditions, participants center their movement endpoints at the center of the target and utilize the entire target. As such, W_E is essentially identical to W. The variability of movements participants produce is equal to the allowed variability of the task.

As W increased across the range of larger levels of W (20, 40, 80 mm) W_E progressively underestimated W. Furthermore, the mean of the distribution of movement endpoints at those conditions undershot the center of the target. It was noted that at all amplitude requirements, the distribution of movement endpoints at larger W conditions undershot the center of the target such that the lower boundary of the distribution tracked, approximately, the inner edge of the target. Tracking the inner edge of the target resulted in minimization of target-to-target travel distance while maintaining a low error rate.

The empirical results from Slifkin and Eder (2016) may be interpreted such that for a given movement time and movement amplitude, there may be a certain amount of variability that the system naturally produces. Under those conditions, when the task demands a reduction in variability, as is the case when W is small (e.g., 5, 10 mm), participants do so by slowing down. When the naturally produced variability is smaller than the allowed variability in conditions, which is the case when W is larger (e.g, 20, 40, 80 mm), instead of electing to further increase their speed and as a consequence increase their variability to encompass the target, participants minimize distance travelled by shifting their distribution of movement endpoints towards the inner edge of the target, undershooting the center. That implies that participants' strategies under those conditions is to minimize distance. Minimizing distance may be reflective of a cost savings for the system. Motor behavior of that nature reflects participants' "knowledge" of their variability, and that participants use that knowledge to calibrate where they aim their movement endpoints. The authors provided evidence for this calibration in an investigation of the relationship between the total unused space in a given condition and CE. Their results indicated that a very strong predictive relationship was found that describes that the degree of undershooting increases as the amount of unused space, or the difference between W and W_E (i.e., W-W_E), increases.

As is the case with many movement tasks, the data of Slifkin and Eder (2016) were all collected under the condition where participants were asked to prioritize speed and accuracy equivalently. It could be the case that under other instructional conditions, the relationship observed between CE and W-W_E might change. Adam (1992), manipulated the emphasis of speed or accuracy by administering different instructions in a cyclic-aiming task. Investigating various kinematic properties of movements participants produced (e.g., acceleration, de-acceleration, dwell time), Adam (1992) found that the nature of movements did not remain constant as a function of instruction.

In other words, movements that had an emphasis on speed did not just have shorter movement times than movements that had an emphasis on accuracy, but also changed in their kinematic properties. Adam (1992) noted that the ratio of movement de-acceleration and acceleration shifted, such that de-acceleration was more pronounced in the accuracy condition. Further, dwell time also increased in the accuracy condition. Adam (1992) found that the task constraints (e.g., W and amplitude requirement) had a larger impact on movements when accuracy is prioritized than when speed is prioritized. Zhai et al. (2004) also manipulated instructions and investigated target utilization when the priorities were shifted between speed, accuracy, and when there was an emphasis on both speed and accuracy. As expected, these researchers found that target utilization varied across the instruction conditions, with the lowest amount of utilization for the accuracy instructions and the highest for the speed instructions. Together, these two studies (Adam, 1992; Zhai et al. 2004) tell us that the relationship between movements and task constraints are modulated by differential priorities for speed and accuracy. As such, it might be interesting to investigate possible differences in the nature of the relationship between undershooting and unused space found in Slifkin and Eder (2016) when the emphasis on speed and accuracy is modulated.

Current Study

In the current study, I investigate the relationship of the total unused space in a target and CE by manipulating task instructions as was done in the previous work outlined above by using a reciprocal targeted aiming task similar to the task used in Fitts (1954). To the best of my knowledge, this is the first study to focus on the means of the distribution of endpoints and their relationship with variability relative to targets, rather than other kinematic properties of movements, while manipulating instructions to differentially emphasize speed and accuracy. In keeping consistent with the extant literature, I adopted a set of explicit task instructions similar to those used by both Adam (1992) and Zhai et al. (2004), with the addition that participants were told they would be given monetary rewards based on their performance to reinforce the appropriate instructional priority. Participants were exposed to 10 unique combinations of five W conditions (5, 10, 20, 40, 80 mm) and two amplitude conditions (80, 160 mm).

As was mentioned above, in Slifkin and Eder (2016), the knowledge of the unused target space could be automatically linked to the degree of shift away from the center of the target. By manipulating instructions either to emphasize accuracy, maintain a balance between speed and accuracy, or to emphasize speed, variability of movement endpoints would differ, and as such the amount of unused space in a target would differ across instruction conditions, allowing further exploration of this relationship. That is, when accuracy is emphasized, variability would decrease and thus the amount of unused space within a target would increase. When speed is emphasized, the opposite should occur, and variability is expected to increase, decreasing the amount of unused space within a target.

A few possible results from these manipulations could be observed: One, as is represented in **FIG. 1**, the relationship between CE and W-W_E is maintained, as is observed in Slifkin and Eder (2016), but the data are range restricted, such that movements in the accuracy condition fall on the slope of the line at one end, while the speed condition data points fall on the slope of the line at the other end. For example, in the accuracy-biased condition, where W_E should be smaller, W-W_E becomes larger, and participants should aim closer to the inner boundary. The opposite would be true in the speed-biased condition. That is, participants would produce different magnitudes of variability across instructions and would use implicit knowledge of their variability to shift their endpoint distributions such that their distributions continue to closely track the inner edge of the target, mimicking the results of Slifkin and Eder (2016). An equivalent relationship across instruction conditions would imply that variability and constant error are "hard" coupled (i.e., the relationship is automatic, direct, and implicit) and that manipulating variability via instructions reliably affects constant error.

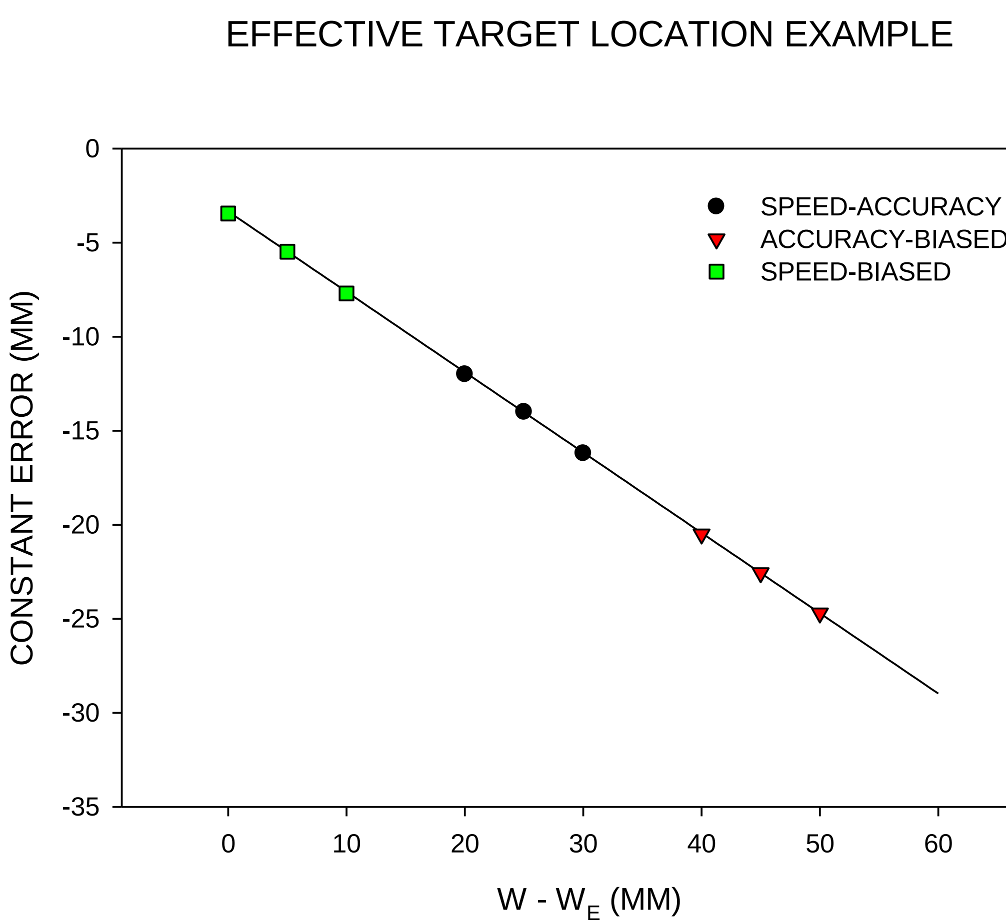

Figure 1. Hypothetical results of the regression analysis of constant error and unused space within a target for all three instruction conditions. Accuracy-biased and speed-biased effective target locations fall on the same slope as speed-accuracy, but are range restricted.

Alternatively, the relationship between CE and W-W_E could change and the slope of the regressions could differ across the instruction conditions. A relationship between CE and variability would be maintained, but the nature of the relationship could differ if the slopes were different. If CE is contingent solely on variability, then in the accuracy-biased condition the slope of the relationship would be steeper, and in the speed-biased condition the slope would be shallower as compared to speed-accuracy. In addition, the degree to which the accuracy-biased instruction condition could differ from the speed-accuracy instruction condition, and the degree to which the speed-biased instruction condition could differ from the speed-accuracy instruction condition, may be different. The magnitude of the difference between accuracy-biased, speed-accuracy, and speed-biased would be informative as it would allow for conclusions regarding how much emphasis participants actually give to speed and accuracy in tasks where both are meant to be equivalently prioritized.

CHAPTER II

METHOD

Participants and Design

Forty-eight healthy individuals from the Cleveland State University community served as participants. The mean age of all the participants was 19.79 (SD = 2.22) years. All participants were right-hand dominant, and reported no prior history of neurological disease or damage. Participants reported normal or corrected-to-normal vision. Participants were recruited from the Department of Psychology's research participant pool and responded to advertisements for healthy right-hand dominant volunteers between the ages of 18-30. Each participant was provided with an informed consent form that had already been approved by Cleveland State University's Institutional Review Board. Upon completion of the experiment, participants received research participation credit toward their classes and an additional monetary incentive of $5.00.

Participants were exposed to one of three between-participants instructional task conditions emphasizing accuracy, both speed and accuracy, or speed. Each group of three consecutive participants coming into the experiment was randomly assigned, without replacement, to one of the three instruction conditions (accuracy-biased, speed-accuracy, speed-biased). There were 16 participants per group, and each group had an equal number of males and females. The mean ages were 19.86 (SD = 2.00) for the accuracy-biased group, 20.50 (SD = 2.85) for the speed-accuracy group, and 19.00 (SD = 1.46) for the speed-biased group. There were no significant age differences between groups. Within each instruction condition group, participants were presented with 10 unique combinations of target amplitude and target width. There were two levels of movement amplitude (80, 160 mm) and five levels of W (5, 10, 20, 40, 80 mm). **FIG. 2** depicts the amplitude requirements and Ws associated with the easiest (top) and most difficult (bottom) conditions. For each combination of amplitude requirement and width, participants were required to move between targets 100 times. As such, the overall design was a 3 (Instruction) x 2 (Amplitude) x 5 (W) mixed model design. Instruction was a between-participants factor, while Amplitude and W were within-participants factors.

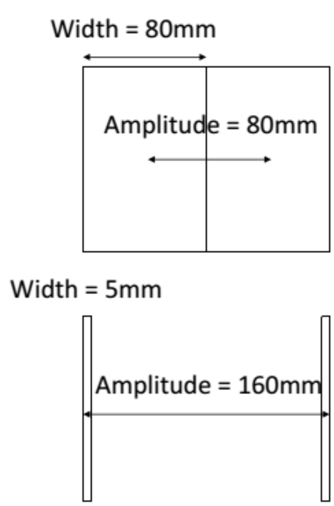

Figure 2. Easiest (top) and most difficult (bottom) conditions.

Apparatus

Hand movements were made on a 305 by 457 mm graphics tablet (Wacom Intuos2) using a cordless mouse (Wacom Intuos2 4D Mouse). The target displays were viewed on a 470 mm flat screen LCD video monitor (ACER X183H) with a refresh rate of 75 Hz. The actual viewable dimensions of the monitor were 230 mm in height by 430 mm in width. The graphics tablet was placed on a table with a height of 743 mm. A stand was also placed on a table and the computer monitor was placed on top of the stand. By placing the computer monitor on the stand, the height of the monitor was raised by 235 mm. At this height, coupled with chair adjustments, the center of the monitor was at eye level for all participants. The tablet was situated directly in front of the monitor. When a participant was seated at the table, his or her body midline was aligned with the midline of the tablet and monitor. Participants were allowed to adjust the chair to a comfortable height and distance from the table; the approximate distance from participants' eyes to the video monitor was 660 mm.

Procedure

Customized software was used to run the experimental conditions and present the target displays. Each target display consisted of two targets that were equidistant from the center of the monitor. The targets appeared as white rectangular outlines surrounded by a black background. Target height was set at 139.70 mm. There were 10 target display conditions, such that each had a unique combination of Amplitude (80, 160 mm) and W (5, 10, 20, 40, 80 mm) values. Depending on their group assignment, participants were instructed either to prioritize accuracy, prioritize both accuracy and speed, or prioritize speed.

Participants ran through the 10 target display conditions in a random order within their assigned instructional group. It was communicated to participants that their performance, specifically how well they prioritized speed or accuracy in their given instruction condition, would determine the amount of extra money – ranging from one dollar to five dollars – they would receive at the end of the experiment. However, regardless of performance, all participants actually received a five dollar payment at the end of the experiment.

During each condition, two target rectangles were presented and 100 consecutive back-and-forth movements between the targets were completed. During that time, a cursor was continuously displayed on the video monitor. The *x*-dimension control-to-display mapping was 1:1, such that a unit of mouse movement along the *x*-dimension of the graphics tablet translated to a unit of cursor movement along the *x*-dimension of the video display. The *y*-dimension control-to-display gain was 1.33:1.00, such that a unit of mouse movement along the *y*-dimension of the graphics tablet resulted in 0.75 units of cursor movement along the *y*-dimension of the video display. All reported data consist of movements from the *x*-dimension. Throughout each movement, data acquisition occurred every 15 or 16 ms (M ≈ 15.5 ms), which translated to instantaneous acquisition rates of either 66.67 or 62.50 Hz (M ≈ 64.52 Hz), respectively. The spatial resolution of each sample was 0.1mm.

At the start of the experimental session, I demonstrated the movement task and simultaneously delivered the task instructions. Participants were instructed that the white crosshairs would serve as a cursor and its position on the video monitor would correspond to the position of the mouse on the graphics tablet. At the start of each movement condition, a white marker, also in the form of crosshairs, appeared in the center of the left target. Participants were told that the marker crosshairs identified the currently active target. It was emphasized that a target hit would register if the cursor crosshairs "lands" anywhere within the active target region at the time of a mouse button press. On the other hand, any button press occurring when the cursor crosshairs was outside of the target was classified as a target miss and would be accompanied by a "beep" sounded by the computer. At the time of either a target hit or a miss, the marker crosshairs would immediately change location to the opposite target, and participants were instructed that they should move to that target and produce a button press when the cursor is in that target region. Participants were told to continue the sequence of back and forth movements until the target display disappeared from the screen. Such an event signaled the end of the sequence of 100 movements. In the accuracy-biased instruction condition, participants were told to "be as accurate as possible; prioritize accuracy over speed." In the speed-accuracy instruction condition, participants were told to "be as fast and as accurate as possible; giving equal priority to both speed and accuracy." In the speed-biased instruction condition, participants were told to "be as fast as possible; prioritize speed over accuracy."

Following delivery of the instructions, participants practiced 50 movements on three target display conditions per their specific instructions. The three practice conditions were chosen randomly out of the 10 possible amplitude requirement and W combination conditions. As during the experiment itself, the order of each participant's three practice conditions was randomized. During the experiment, participants were required to rest for five minutes at the end of the third and seventh experimental conditions. Depending on the instructions participants were exposed to, the total session duration ranged from 30 to 90 minutes. Participants in the accuracy-biased group took longer to complete the experiment and those in the speed-biased group took less time to complete the experiment. During both practice and experimental conditions the overhead lights were extinguished. However, for the initial practice condition a small lamp was left on. Thus, the only task-related visual information available to participants were the stimuli presented on the video screen (i.e., the cursor and the target displays). In addition, participants wore sound-attenuating earmuffs during experimental trials in order to minimize the potential influence of sound extraneous to the experiment. The volume of the computer-generated error "beep" was adjusted so that participants could hear it through the earmuffs.

CHAPTER III

DATA PROCESSING AND ANALYSIS

The initial 10 movements of each experimental condition were not analyzed, thereby excluding warm-up and cross-over effects (i.e., any performance hindrance that could arise from the task constraints from the previous trial) that may have been present during the initial portion of the condition. Of the remaining 90 movements, outliers were then removed using the MAD-Median method such that endpoints that were greater than 3 median absolute deviations (MAD) from the median endpoint were removed. In addition, movements with movement times greater 3 median absolute deviations (MAD) from the median movement time were also removed. Wilcox (2012) suggests that this method is more robust than the typical removal methods that are based on standard deviations. The outliers removed tended to be movements made to the wrong target – most commonly due to double clicks, and movements where participants paused in the middle of movement not due to any task constraints. From the total movements made by all participants, 5.8% of data points were removed. The movement amplitude that participants produced was defined as the distance, along the *x*-axis, between the location of the mouse click that terminated movement at the previous target to the location of the mouse click that terminated movement at the current target. The time between those mouse clicks was the movement (MT). That is, $MT_x = t_x - t_{(x-1)}$, where x is the movement, and t is the time, in milliseconds, from the start of the condition. The analysis of mean MT provided information about how well the participants complied with the instructions.

For each condition, participants produced a distribution of movement endpoints (i.e., the positional x-coordinates registered at the location of each mouse click). The difference between each individual movement endpoint and the center of the target was defined as the constant error (CE) for that movement. The mean for the individual CE values were then calculated to obtain the CE for a specific condition. CE is reflective of where participants aim.

Effective target width (W_E) is defined as the central 96% of the spread of endpoints. This can be measured in standard deviation units (σ) of the distribution of endpoints. Specifically, W_E is defined as: $\sqrt{2\pi e}\sigma = 4.1325\sigma$ (Zhai et al., 2004). The main indicator of target utilization used in this study was one adopted from the Slifkin and Eder (2016) study. Namely, the difference between W and W_E as a measure of the magnitude of the unused area in a condition.

Main Analyses

For the main analysis, a mixed-model repeated-measures 3 (Instruction) x 2 (Amplitude) x 5 (Width) ANOVA was performed investigating MT, CE, and W_E. Instruction condition was a between-participants factor. Both Amplitude and W were within-participants factors. Importantly for this study, a linear regression was performed between CE and the difference between W and W_E for each Amplitude and W combination for all Instruction groups. This regression analysis served to establish if the relationship described in the Slifkin and Eder (2016) applied to all three Instruction groups.

CHAPTER IV

RESULTS

Movement Time

Collapsing across W and Amplitude, the mixed model 3 x 2 x 5 repeated measures ANOVA revealed a significant main effect for instruction, $F(2,45) = 14.60$, $p < .001$, $\eta_p^2 = 0.393$. Planned contrasts revealed that participants that were provided with accuracy-biased instructions had slower movement durations (M = 1236.84 ms, SD = 554.78) than participants exposed to the speed-accuracy instructions (M = 742.11 ms, SD = 141.42). No differences were observed between the participants exposed to the speed-accuracy instructions and the speed-biased instructions (M = 620.79 ms, SD = 149.83). In addition, replicating previous research (e.g., Fitts, 1954; Meyer et al., 1988; Schmidt et al. 1979; Zhai, 2004), Ws and amplitude requirements also had an effect on movement times. Collapsing across Instructions and W, the main effect for Amplitude, $F(1,45) = 172.93$, $p < .001$, $\eta_p^2 = 0.794$, revealed that participants had longer movement durations as the amplitude requirement increased from 80 mm (M = 760.64 ms, SD = 382.86) to

160 mm (M=972.52 ms, SD=478.54). A main effect for W was also observed, $F(4, 180) = 444.13$, $p < .001$, $\eta_p^2 = 0.908$. **FIG. 3** depicts movement times as a function of W for each of the instruction conditions. As W conditions increased from the smallest (5 mm) to the largest (80 mm) values, movement durations were significantly reduced at each step.

An Amplitude x Instruction condition interaction was observed, $F(2,45) = 3.93$, $p < .05$, $\eta_p^2 = 0.148$, indicating that participants in the accuracy-biased condition showed a greater magnitude of difference in MT compared to the other two instruction conditions as the amplitude requirement increased. A W x instruction condition interaction, $F(8, 180) = 13.36$, $p < .001$, $\eta_p^2 = 0.373$, indicating that the magnitude of the difference between the accuracy-biased condition compared to the other two conditions decreased as W increased. Finally, an Amplitude x W interaction, $F(4,180) = 6.01$, $p < .001$, $\eta_p^2 = 0.118$, evidenced that MT differences between the two amplitude requirement conditions converged as W increased.

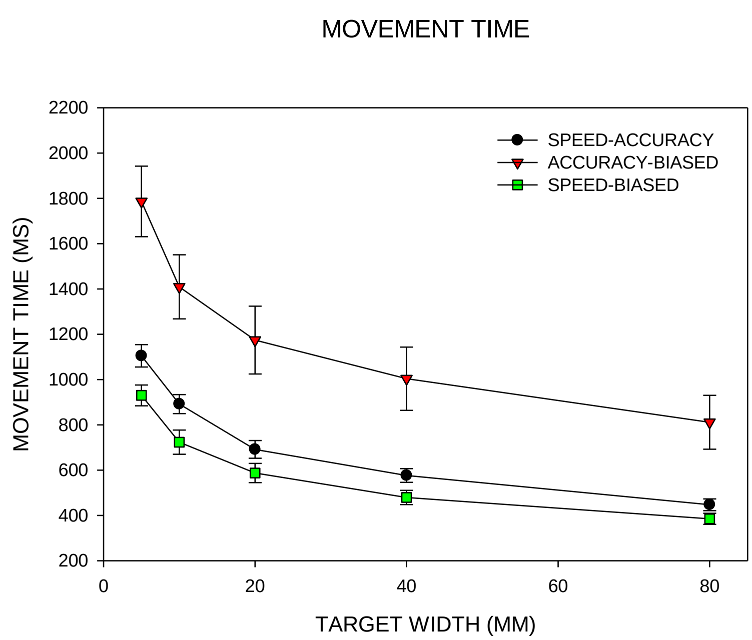

Figure 3. Movement time as a function of target width for all instruction conditions.

Constant Error

A mixed models 3 x 2 x 5 repeated measures ANOVA was performed investigating constant error for all conditions. A main effect for Instruction condition was observed, $F(2,45) = 5.80$, $p < .01$, $\eta_p^2 = 0.205$. Planned contrasts revealed that participants exposed to the accuracy-biased instructions (M= -4.22 mm, SD = 2.53) undershot the center of targets less so than participants that were exposed to speed-biased instructions (M = -7.08 mm, SD = 2.44). The difference between participants exposed to the speed-accuracy (M= -6.08 mm, SD=2.25) instructions and the speed-biased instructions did not reach significance (p = 0.24). A large main effect for W was found, $F(4,180) = 287.23$, $p < .001$, $\eta_p^2 = 0.864$. **FIG. 4** depicts CE as a function of W collapsed across amplitudes. The dotted line represents a CE value of 0 which would indicate the center of the target. All data points fell below the dotted line and indicate that participants undershot the center of the target for all conditions. CE varied reliably as a function of W such that as W increased, participants produced more negative CE. That is, participants undershot the center of the target to a greater degree as W increased in size. Importantly, there was a significant interaction between W and Instruction condition, $F(8,180) = 5.48$, $p < .001$, $\eta_p^2 = 0.196$. Coupled with the results of W_E discussed below, these results are informative regarding the main questions of this study and will be discussed further.

An Amplitude x Instruction condition interaction was found, $F(2,45) = 4.34$, $p < .05$, $\eta_p^2 = 0.162$, indicating that the magnitude of the difference between the accuracy-biased conditions and the other two conditions decreased as amplitude requirement increased. An Amplitude x W interaction, $F(4,180) = 25.41$, $p < .001$, $\eta_p^2 = 0.361$, revealed that the differences in CE between amplitude levels increased as the W increased. Specifically, at 5, 10, 20, and 40 mm, the CE error values were similar, but a relatively large difference emerged at the 80 mm W condition. A three way Instruction x Amplitude x W interaction was also observed, $F(8,180) = 2.94$, $p < .01$, $\eta_p^2 = 0.115$, indicating that there was a magnitude difference in CE between instructional conditions for the 80 mm W – 80 mm amplitude requirement target and the 80 mm W – 160 mm amplitude requirement target in so far as the difference between instructions was attenuated at the higher amplitude requirement condition.

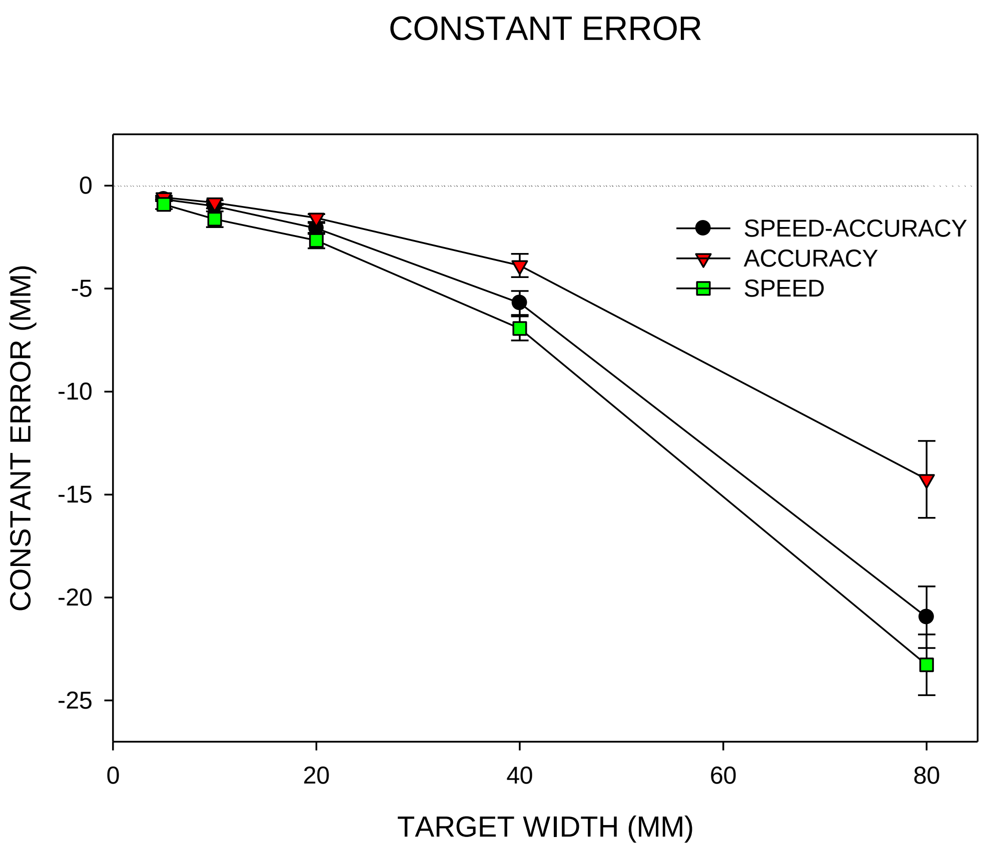

Figure 4. Constant error as a function of target width collapsed across amplitude requirements. The dotted line represents a constant error value of 0, which would indicate the center of the target. All data points are below the dotted line and indicate that participants undershot the center of the target for all conditions.

Effective Target Width

A mixed model 3 x 2 x 5 repeated measures ANOVA investigating W_E, as predicted, established main effects for all three factors. Collapsing across W and Amplitudes, the main effect of Instructions, $F(2,45) = 24.81$, $p < .001$, $\eta_p^2 = 0.524$, and the subsequent planned contrasts revealed that participants' W_E differed between accuracy-biased (M = 10.70 mm, SD = 2.68), and the speed-accuracy (M = 15.98 mm, SD = 4.48) instructions. Additionally, W_E differed between speed-accuracy and speed-biased instructions (M = 22.26 mm, SD = 6.12). Participants exposed to the accuracy-biased instructions produced the smallest W_E. Participants exposed to the speed-accuracy instructions produced the next smallest W_E, while participants exposed to the speed-biased instructions produced the largest W_E. A main effect for Amplitude was also observed, $F(1, 45) = 84.97$, $p < .001$, $\eta_p^2 = 0.654$. This effect indicates that participants produced larger W_E when the amplitude requirements increased from 80 mm (M=14.06 mm, SD=6.39) to 160 mm (M=18.56 mm, SD=7.28).

The main effect of W, $F(4,180) = 178.28$, $p < .001$, $\eta_p^2 = 0.798$, revealed that W_E increased as target width increased such that participants produced the smallest group-mean W_E for the smallest W condition, and produced the largest group-mean W_E at the largest W condition. **FIG. 5** depicts participants' averaged W_E collapsed across amplitude requirements for each instruction condition at the various W levels. The dotted diagonal line represents the values at which W_E equals W. Thus, data points above the line represent observations where W_E was larger than W. Data points below the line represent observations where W_E was smaller than W. The interaction between W and Instruction condition did not cross the threshold for statistical significance, $F(8,180) = 1.91$, $p = .06$, $\eta_p^2 = 0.078$. The marginal significance of the W x Instruction interaction for W_E is in contrast with CE and illustrates that instruction conditions had a differential impact on CE and W_E at the different width levels.

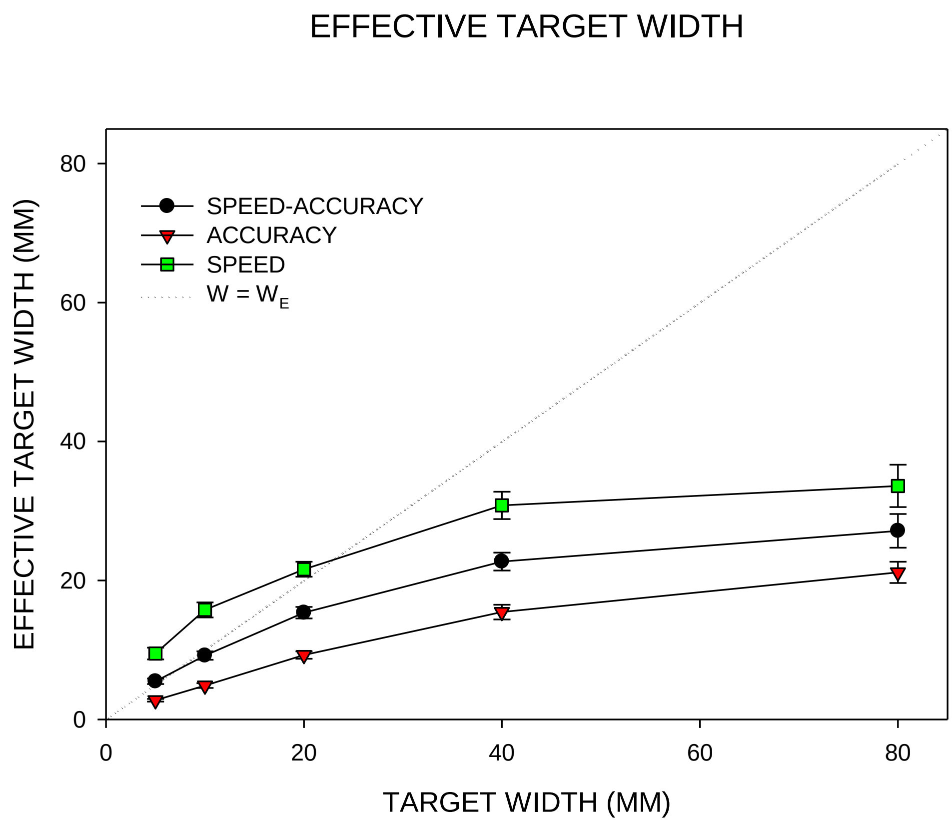

Figure 5. Effective target width as a function of target width. The dotted line indicates the point at which effective target width and target width is equivalent. Data points above the line indicate that effective target width is larger than target width. Data points below the line indicate that effective target width is smaller than target width.

W-W_E vs. Constant Error

In order to further explore the interactions observed above, following Slifkin and Eder (2016), I describe the relationship between unutilized space (W-W_E) and constant error for the different instruction conditions. **FIG. 6** depicts the relationship of the total unused space in a target and the degree of undershooting for the 10 task constraint conditions (i.e., the 10 different combinations of amplitude requirement and W) for participants exposed to: a. the accuracy-biased instructions, b. the speed-accuracy instructions, c. the speed-biased instructions. The regression coefficients and r^2 values are listed on Table 1. The slope analysis was conducted using the following equation, $t = \frac{b_1 - b_2}{\sqrt{s_{b_1}^2 - s_{b_2}^2}}$. The analysis revealed that the nature of the relationship between constant error and $W\text{-}W_E$ was different between the accuracy-biased instruction condition and both the speed-accuracy instruction condition [$t(16) = 5.90$, $p < .001$] and the speed instruction condition [$t(16) = 6.90$, $p < .001$]. The slopes did not statistically differ between the speed-accuracy instruction condition and the speed instruction condition, though the difference was in the vicinity of statistical significance, $t(16) = 1.74$, $p = .10$. Thus, while not all comparisons were significant, the slope values increased from accuracy-biased to speed-accuracy to speed-biased. It should be noted that the r^2 values for all instruction conditions were high, ranging from .96-.99. As such, a strong relationship is maintained regardless of instruction condition, but slope differences indicate that the nature of the relationship shifts, particularly for the accuracy-biased instruction condition.

Table 1.

Slopes and r^2 values for the regressions analysis of CE and $W\text{-}W_E$

	Instructions		
	Accuracy-Biased	Speed-Accuracy	Speed-Biased
Intercept	0.74	-0.33	-3.35
Slope	-0.24	-0.38	-0.43
r^2	0.96	0.99	0.98

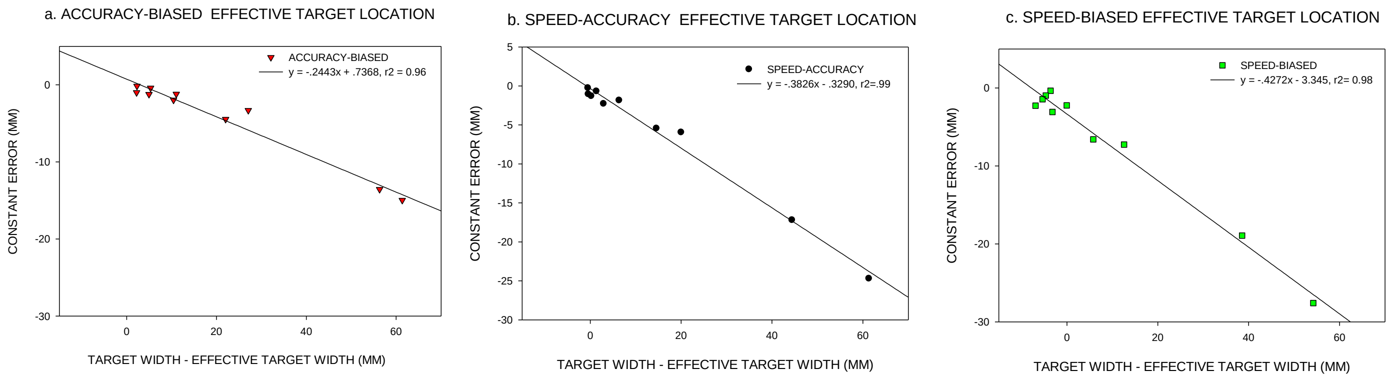

Figure 6. Regression analysis of constant error and unused space within a target for: a. accuracy-biased instruction condition, b. speed-accuracy instruction condition, and c. speed-biased instruction condition.

CHAPTER V

DISCUSSION

The main purpose of introducing different instruction conditions was to modulate the variability participants produced, thus enabling a more thorough examination of CE and W_E. The results demonstrate that the instruction conditions appropriately affected movements. Accuracy-biased instructions resulted in the least amount of variability, followed by speed-accuracy instructions, and speed-biased instructions resulted in the greatest amount of variability. Together with constant error values, the results of this study replicate and extend Slifkin and Eder (2016). At all but the smallest Ws, the means of movement endpoint distributions consistently undershot the center of the targets. In addition, the degree of this undershooting scaled with increases in W such that the magnitude of undershooting became progressively greater as W increased from the smallest to largest values. Further, as undershooting increased at the larger W values, W_E was no longer equivalent to W. That is, participants did not use all of the target to make their movements, in any of the three instruction conditions.

The primary analysis, investigating the effect of instruction condition on the nature of the relation between CE and W-W_E, revealed interesting results. First, across all three conditions, there was a strong relationship as evidenced by the r^2 values, ranging from .96 to .99. For all three conditions, as W-W_E increased (i.e., as less of the target was used) participants undershot the center in a progressively greater fashion; thus, the results from Slifkin and Eder (2016) were replicated here. Comparing the slopes of the regression equations, speed-accuracy instructions and speed-biased instructions, statistically, led to the same relationship between W-W_E and CE. However, accuracy-biased instructions changed the relationship as compared to both speed-accuracy and speed-biased instructions. Two possibilities were previously addressed regarding the impact of instructions on the relationship. First, the slopes of the regressions would be equivalent and a similar relationship would be shared among all three instruction conditions. In this case, the data from the three groups would differ only in that they fall on different points on the same regression line. Second, the slopes of the regression equations would be different and the magnitude of the relationship found in the speed-accuracy conditions could would differ. **FIG. 7** makes it apparent that, while variability relative to W (i.e., W-W_E) and CE shared a strong relationship across instruction conditions, the slope of this relationship in the accuracy-biased instruction condition differed. The different symbols represent the means of the movement distributions participants produced at the different instruction conditions. The error bars denote the size of $W_{E,}$ or 96% of movement endpoint distribution. Combined, those two illustrate *effective target*, which is defined as the location and task work-space that participants actually use when making their movements. For all conditions, as the amount of unutilized space in a target increased the distribution of endpoints shifted away from the center, closer to the inner edge of the target. The slope analysis revealed that while this general trend remained true for all conditions, the shift away from the center was less pronounced for the accuracy-biased instruction condition. That is, even though there was more unused space, undershooting was attenuated when participants were instructed to emphasize accuracy. The results contrast with the prediction made at the outset of this study. If participants' knowledge of their variability was the only factor in aiming, then a smaller range of movement endpoints would lead to greater undershooting in the accuracy-biased condition, but the opposite was observed. Additionally, while the slope analysis did not reveal any significant differences between the speed-accuracy condition and the speed-biased condition, there was a tendency toward an effect (p = .10). There was less unused space in the speed-biased condition than the speed-accuracy condition across all target widths. Given that, if the relationship was absolutely equivalent, then the distributions should be shifted toward the center of the target compared to the speed-accuracy condition. While not statistically different, there was a general trend for the opposite (i.e., distributions were shifted further away from the center in the speed-biased condition).

While these results may seem counterintuitive at first, with respect to what would be expected with changes in variability across groups, they are not necessarily so. The implicit knowledge of variability relative to the target width did impact aim points (i.e., CE), but a second factor also played a role, that of the explicit instructions. Note again, instructions were introduced to manipulate variability and thereby influence the implicit mechanisms behind aiming. However, because of the nature of this manipulation, participants were made explicitly aware that hitting the target (accuracy-biased condition), or making fast movements (speed-biased condition), was preferable. Thus an interplay between implicit and explicit mechanisms emerged, such that the implicit knowledge of variability relative to target width still led to consistently progressive undershooting, but the explicit demands of the task changed the magnitude of undershooting. The explicit demands of the task may be more evident when looking at the differences between the inner actual target boundary and lower boundary of W_E. That is, it seems to be the case that as instructions went from an speed emphasis to an accuracy emphasis, participants shifted the lower boundary of their distribution of movement endpoints further away from the inner edge of the target at all W values.

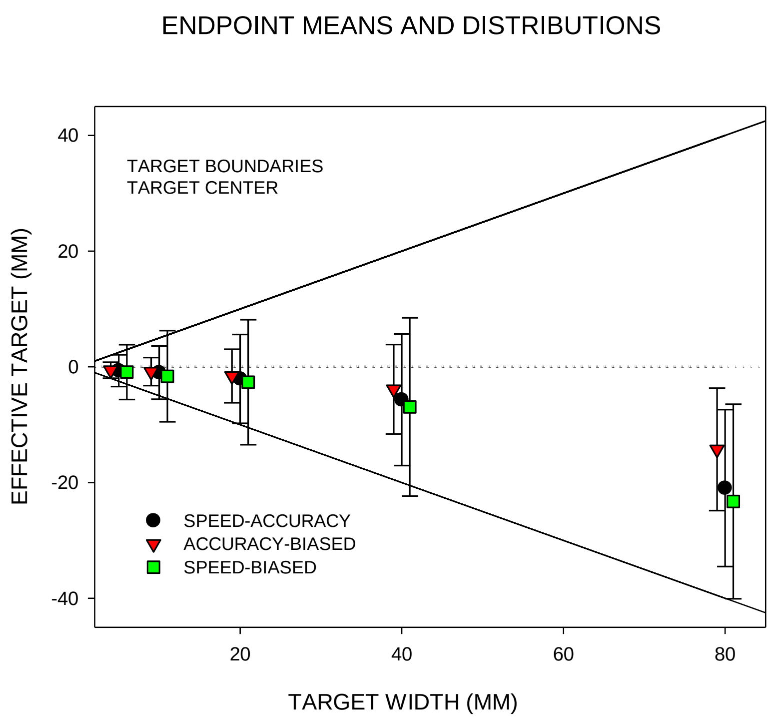

Figure 7. *Endpoint means and distributions of participants for all three instruction conditions. The geometric symbols represent means of the distribution for the appropriate instruction condition. Error bars indicate 96% of the range of movements made.*

Adam (1992), provided evidence that participants' movements, when instructions to be accurate are emphasized compared to when instructions to be fast are emphasized, are not only different in movement durations, but are also different in their kinematic properties, such that deceleration periods and dwell times are also increased as accuracy was emphasized. Here, we see evidence that differences arise not only in the kinematics of the movement itself, but also in the location at which participants choose to aim. The choice to aim closer to the center of the target, despite the implicit tendency to undershoot, may have to do with a risk analysis influenced by explicit instructions and the feedback participants received. Neyedli and Welsh (2013) showed that when externally imposed performance feedback is provided, participants are prone to shift their aim points toward less perceived risky locations, even when their variability allows them to make more optimal movements. In this study, participants were informed that additional payment would be received provided they performed well in a given instruction condition. Thus, there was risk associated with missing the target in the accuracy-biased condition and being slow in the speed-biased condition. Gepshtein et al. (2007) provide evidence that participants are able to reliably modulate aim points depending on the riskiness of locations in a condition. In their paradigm, participants were tasked to point to circular targets while avoiding penalty regions that were also circular. Target regions and penalty regions would overlap in a given condition. Participants shifted their aim points from the center of target regions opposite to that of the penalty regions. In comparison, in this study, for the accuracy-biased condition the penalty region would be any location outside of the boundaries of the target. Thus, while variability was smaller in the accuracy-biased condition than in both the speed-accuracy and speed-biased conditions, participants chose to aim at less risky locations closer to the center of the target and away from the target boundaries.

One possible reason we see a greater difference between the accuracy-biased condition and the speed-accuracy condition, as compared to the speed-biased condition and the speed-accuracy condition, is that there is more flexibility to modulate accuracy than there is with speed. That is, participants in the accuracy-biased condition may be willing to limit their variability by slowing down; conversely, participants who are in the speed-biased condition are less willing to speed up their movements up further and decrease their hit rate. In general, planned movements may implicitly have a greater weight on accuracy than speed. Quickly moving to grasp a cup is useless if the movement is so quick that you miss the cup entirely. Additionally, most movement tasks provide more salient feedback for accuracy than for speed. That is, participants are more aware about whether or not they hit a target than they are about how quickly they did so. Similarly, in this task, for the initial starting conditions, irrespective of instructions, there may be a bias towards accuracy. Further, when participants made errors, that is when they missed the target, a beep was played indicating that an error was made. No equivalent feedback was given when movements were slow.

The concept of feedback modulating characteristics of movements has been well studied (Ankarali et al., 2014; Brenner & Smeets, 2011; Diedrichsen, Shadmehr, & Ivry, 2010; Siegler et al., 2010; Slifkin & Eder, 2012; Loeb et al., 1990).   The optimal feedback control theory (OFCT) described in Todorov and Jordan (2002) claims that the characteristics of movements change based on feedback given only in the relevant domain. For example, if feedback was only given about *x*-coordinate movements in a given task, variability in the *x*-coordinate domain would be modulated as a result of feedback, but *y*-coordinate variability would not be affected. Beers (2009), provided evidence for this phenomenon by varying the degree of feedback given in a movement task. Participants varied in how much they corrected their movements based on the degree of feedback. As such, if the degree of feedback for accuracy and speed were different in a task, variability would be modulated more so in the domain that was given more feedback. In this study, while there is a difference in aim points between accuracy-biased participants and speed-accuracy participants, we see no difference between speed-accuracy participants and speed-biased participants. Based on OFCT, participants would modulate their movements to maintain hit rate irrespective of instruction condition, over and above modulating their speed. This is reflective of a follow-up hit rate analyses that indicated that even though differences emerged between speed-biased participants and the other two groups, the overall hit rate for those participants was still quite high (85%). Thus, we see greater shifts toward accuracy for the accuracy-biased participants than we see shifts to speed in the speed-biased participants.

The consistent undershooting and underutilization of target space at W conditions above 10 mm suggests the stochastic optimized submovement model is incompatible with performance under larger W conditions. An alternative model is proposed by Harris and Wolpert (1998), the minimum variance model, and argues that the motor system for arm movements operates in such a way as to minimize *signal-dependent* variance in endpoints. The assumption Harris and Wolpert (1998) make is that variance increases as the mean level of the signal required to produce a movement increases. That is, the noise inherent in the biological system increases as the force required to make a movement increases. Note, increased force can result in either increased speed, distance, or a combination of both. Thus, for any given movement speed and amplitude requirement, it is possible that the system expresses a base level of variability. Thus, for a given task, performance approaches optimality by either forcefully reducing variability from its base level, or by reducing amplitude traveled. According to this possibility, the task constraints dictate the strategy chosen. Participants engage in distance-minimizing strategies if the allowed variability in a task is greater than the base variability of the system. Alternatively, if variability needs to be reduced, participants do so by slowing down or increasing movement durations (Fitts, 1954; Schmidt 1979). In this task, it could be that for Ws of 5 mm and 10 mm, the base level of variability set by the force requirements of the movement is larger than what the task demands allow. In these conditions, variability must then be scaled down by increasing movement durations. In conditions where target widths are larger than the base level of variability, participants elect to become more optimal by shifting their distribution such that they start to track the inner edge of the target.

To conclude, movement endpoint profiles are influenced by a confluence of factors. First, greater emphasis on speed or accuracy, particularly accuracy, modulated aiming, such that participants produced lower variability but did not take advantage of this by shifting closer to the inner edge of the target. Accuracy-biased participants would have been able to maintain their hit rate in doing so, but instead they elect to aim their movements at a location that is closer to the center and less risky. Second, the strategies employed by participants are two-fold based on movement variability: 1) when variability is larger than W, participants elect to reduce their variability by slowing down and aim at the center in order to maximize hits; 2) when variability is smaller than W, participants elect to save time and effort by undershooting the center of the target. Third, asymmetrical bias toward accuracy is accounted for by the general need to hit a target in most movements and the different levels of feedback provided in this task. This third influence on movements observed in this task can be manipulated, and future studies should examine whether greater feedback in the time domain would balance out the inherent bias towards accuracy.

REFERENCES

Adam, J. J. (1992). The Effects of Objectives and Constraints on Motor Control Strategy in Reciprocal Aiming Movements. *Journal of Motor Behavior, 24*, 173-185.

Ankarali, M. M., Sen, H. T., De, A., Okamura, A. M., & Cowan, N. J. (2013). Haptic feedback enhances rhythmic motor control by reducing variability, not improving convergence rate. *Journal of Neurophysiology, 111*, 1286-1299.

Beers, R. J. (2009). Motor Learning Is Optimally Tuned to the Properties of Motor Noise. *Neuron, 63*, 406-417.

Brenner, E., & Smeets, J. B. (2011). Quickly 'learning' to move optimally. *Experimental Brain Research, 213*, 153-161.

Churchland, M. M., Afshar, A., and Shenoy, K.V. (2006). A central source of movement variability. *Neuron, 52*, 1085–1096.

Diedrichsen, J., Shadmehr, R., & Ivry, R. B. (2010). The coordination of movement: Optimal feedback control and beyond. *Trends in Cognitive Sciences, 14*, 31-39.

Elliott, D., Hansen, S., Mendoza, J., & Tremblay, L. (2004). Learning to optimize speed, accuracy, and energy expenditure: A framework for understanding speed–accuracy relations in goal-directed aiming. *Journal of Motor Behavior*, 36, 339–351.

Elliott, D., Hansen, S., & Grierson, L. E. M. (2009). Optimizing speed and energy expenditure in accurate visually directed upper limb movements. *Ergonomics, 52*, 438–447.

Elliott, D., Hansen, S., Grierson, L. E. M., Lyons, L., Bennett, S. J., Hayes, S. J. (2010). Goal-directed aiming: Two components but multiple processes. *Psychological Bulletin, 136*, 1023-1044.

Elliott, D., Helsen, W. F., & Chua, R. (2001). A century later: Woodworth's (1899) two-component model of goal-directed aiming. *Psychological Bulletin, 127*, 342-357.

Engelbrecht, S. E., Berthier, N. E., & O'Sullivan, L. P. (2003). The undershoot bias: Learning to act optimally under uncertainty. *Psychological Science, 14*, 257–261.

Fitts P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology, 47*, 381-391.

Gepshtein, S., Seydell, A., & Trommershauser, J. (2007). Optimality of human movement under natural variations of visual-motor uncertainty. *Journal of Vision, 7*, 13-13.

Grosbois, J. D., Heath, M., & Tremblay, L. (2015). Augmented feedback influences upper limb reaching movement times but does not explain violations of Fitts' Law. *Frontiers in Psychology, 6,* 800.

Harris, C. M. & Wolpert, D. M. Signal-dependent noise determines motor planning. *Nature, 394*, 780–784 (1998).

Loeb, G., Levine, W., & He, J. (1990). Understanding Sensorimotor Feedback through Optimal Control. *Cold Spring Harbor Symposia on Quantitative Biology, 55*, 791-803.

Lyons, J., Hansen, S., Hurding, S., & Elliott, D. (2006). Optimizing rapid aiming behaviour: Movement kinematics depend on the cost of corrective modifications. *Experimental Brain Research, 174,* 95–100.

MacKenzie, I. S., 1991. *Fitts' law as a performance model in human–computer interaction.* Unpublished Doctoral Dissertation, University of Toronto, Toronto, Canada.

Maloney, L. T., Trommershäuser, J., Landy, M. S., & Gray, W. D. (2007). Questions without words: A comparison between decision making under risk and movement planning under risk. In *Integrated models of cognitive systems*. New York: Oxford University Press.

Meyer D. E., Abrams R. A., Kornblum S., Wright C. E., Smith J. E. K., (1988). Optimality in human motor performance: Ideal control of rapid aimed movements. *Psychological Review, 95*, 340-370.

Neyedli, H. F., & Welsh, T. N. (2013). Optimal weighting of costs and probabilities in a risky motor decision-making task requires experience. *Journal of Experimental Psychology: Human Perception and Performance, 39,* 638-645.

Schmidt R. A., Zelaznik H. N., Hawkins B., Frank J. S., Quinn J. T. (1979). Motor output variability: a theory for the accuracy of rapid motor acts. *Psychological Review, 86*, 415–451.

Seydell, A., Mccann, B. C., Trommershauser, J., & Knill, D. C. (2008). Learning Stochastic Reward Distributions in a Speeded Pointing Task. *Journal of Neuroscience, 28,* 4356-4367.

Siegler, I. A., Bardy, B. G., & Warren, W. H. (2010). Passive vs. active control of rhythmic ball bouncing: The role of visual information. *Journal of Experimental Psychology: Human Perception and Performance, 36,* 729-750.

Slifkin A. B., Eder J. R. (2012). Amplitude requirements, visual information, and the spatial structure of movement. *Experimental Brain Research, 220*, 297-310

Slifkin, A. B., Eder J. R. (2016). *Degree of target utilization influences the location of movement endpoint distributions.* Manuscript submitted for publication.

Todorov E., Jordan M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience 5*:1226–1235.

Trommershäuser, J., Landy, M., & Maloney, L. (2003). Statistical decision theory and trade-offs in the control of motor response. *Spatial Vision, 16*, 255-275.

Wilcox, R. (2012). Modern statistics for the social and behavioral sciences: a practical introduction. CRC Press, Boca Raton, FL.

Woodworth, R. S. (1899). The accuracy of voluntary movement. *Psychological Review, 3*, 1–114.

Zhai, S., Kong, J., Ren, X. (2004). Speed-accuracy trade-offs in Fitts' law tasks--On the equivalency of actual and nominal pointing precision. *International Journal of Human-Computer Studies, 61*, 823-856.