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Optimization in manual aiming: relating inherent variability and target size, and its influence on tendency

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Optimization in manual aiming: relating inherent variability and target size, and its influence on tendency

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Abstract

For manual aiming, the optimized submovement model predicts a tendency toward target-centre of primary movement endpoints (probabilistic strategy) (Meyer et al., 1988), while the minimization model predicts target undershooting (“play-it-safe” strategy) (Elliott et al., 2004). The spatial variability of primary movement endpoints directed toward a cross-hair (400-500 ms) (Session 1) were scaled by a multiplicative factor (x1-4) to form circular targets of different sizes (Session 2). In recognition of both models, it was predicted that the more that inherent variability exceeded the target size, the greater the tendency to shift from target-centre aiming to target undershooting. The central tendency of primary movement endpoints was not influenced by the targets, while it neared target-centre. These findings concur with a probabilistic strategy, although we speculate on factors that might otherwise foster a “play-it-safe” strategy.

Keywords: minimization; optimized; submovement; undershooting

Introduction

Since the early work of Woodworth (1899), it has been broadly understood that manual aiming movements performed toward a distant target are comprised of two identifiable components. There is an *initial impulse*–as characterised by the primary movement–that sees the performer generate a ballistic movement covering a large portion of the required amplitude. This initial phase is followed by *current control*–as characterised by the secondary submovement(s)–that corrects for any error accumulated across the primary movement trajectory courtesy of online or concurrent sensory feedback. The need for such a correction is due to the spatial error manifesting from inherent noise within the central nervous system (Faisal et al., 2008), and/or inadequate programming of the primary movement (Elliott et al., 2001; see also, van Beers, 2009).

The logic behind two component movements is highlighted by the ubiquitous phenomena of a trade-off between speed and accuracy. That is, when movements are too fast, they are less accurate (i.e., more endpoint variability), and when movements are extremely accurate (i.e., less endpoint variability), they are much slower (Fitts, 1954; Fitts & Peterson, 1964; Schmidt et al., 1979). This trade-off can be particularly problematic when we consider how often daily tasks involve aiming movements that are required to be both fast and accurate (e.g., pressing a light switch, typing on the keyboard, etc). Thus, it is of interest to examine how performers contend with this trade-off and optimize their movements; that is, to ensure rapid aiming movements whilst continuing to successfully reach the intended target.

One such explanation is offered by the *optimized submovement model* (Meyer et al., 1988). Broadly speaking, this model contends that performers generate movement velocities that are adequate for minimizing overall movement time while avoiding a time-consuming secondary corrective submovement. The modulation of this initial limb velocity ensures that there is at least some limit to the spatial error induced by signal-dependent noise (as indicated by within-participant standard deviation in the spatial location; also referred to as spatial variability) (Schmidt et al., 1979). In this regard, the primary movement endpoints across a series of trials can assume a distribution with the central tendency located near target-centre, and tail-ends situated less than or near the outer edges of the target boundaries (see Figure 1a and 1b). This model optimizes speed and accuracy because performers can maximize their chances of reaching inside the target, including those instances where their movement trajectories deviate from the target-centre.

However, an alternative view is offered by the *minimization model* (Elliott et al., 2004; Elliott et al., 2009; see also, Elliott et al., 2017). Here, performers modulate the location of their primary movement endpoint in order to limit the time and energy-expenditure of any subsequent secondary corrective submovement. Specifically, the distribution of primary movement endpoints over a series of trials is centred at a location short of target-centre (see Figure 1c; see also, Engelbrecht et al., 2003; Welsh et al., 2007; Worringham, 1991). Consequently, performers are able to definitively avoid moving beyond the target, and with that, the need for a secondary corrective submovement to reverse the limb direction by overcoming inertia and switching the agonist and antagonist muscle functions (Burkitt et al., 2017; Elliott et al., 2014; Lyons et al., 2006; Roberts et al., 2016; see also, Oliveira et al., 2005). Thus, while all categories of secondary corrective submovements are more time- and energy-consuming compared to directly hitting the target (i.e., single component movement), the corrections to undershoots are less costly to time and energy than those to overshoots (Elliott et al., 2004; Roberts et al., 2018).

However, owing to increased task exposure and trial-and-error learning, there may be a decline in the spatial variability that is associated with a programming error (Burkitt et al., 2015; Elliott et al., 2004; Hansen et al., 2005; Müller & Sternad, 2004; Neyedli & Welsh, 2013). Herein, performers may progressively undershoot less over a series of trials due to the reduced need for any secondary corrective submovement, which effectively represents performers "sneaking-up" on the target (Elliott et al., 2004; see also, Abrams & Pratt, 1993; Pratt & Abrams, 1996). At this point, it could be argued that the distribution assumed by the *minimization model* begins to resemble that of the *optimized submovement model* (see Figure 1b and 1d).

[Insert Figure 1 about here]

Of interest, these models have in common the influence of variability on the primary movement with a view to limiting the need for a secondary corrective submovement (see also, Hamilton & Wolpert, 2002; Harris & Wolpert, 1998; Trommershäuser et al., 2005). Implicit within this assumption is the influence of the target size, and more specifically, its relation to the distribution of primary movement endpoints. That is, the degree of closeness or overlap between the width of the target and spatial variability may cause the central tendency of primary movement endpoints to shift accordingly (see also, Trommershäuser et al., 2003). For example, as outlined by the *optimized submovement model*, the tendency should be to reach for the centre of the target when the distribution of primary movement endpoints is predicted to subtend the target boundaries because even the tails of the distribution can enter within the target boundaries. However, as outlined by the *minimization model*, the tendency should be to undershoot when the distribution that follows a reach to the centre of the target is no longer predicted to subtend the target boundaries because the tails of the distribution begin to "spill-over" and produce an unfavourable number of overshoots.

To date, the available evidence appears to be consistent with the *minimization model* as undershoots are more prevalent in the presence of small compared to large targets (Roberts, 2020; for an alternative perspective, see Dounskaia et al., 2005; Fradet et al., 2008a). That said, there is also evidence of inversely more undershooting that lands nearer the target edges for very large targets (e.g., 8 cm) (taken with respect to the terminal movement endpoint; Slifkin & Eder, 2017). The present study attempted to disambiguate predictions made by the *optimized submovement model* and *minimization model* by examining the central tendency of primary movement endpoints involving target sizes that were scaled according to the participants' own inherent variability (i.e., effective target width, synonymous with ~95% of the distribution; Welford, 1968). The inherent variability was assessed by initially using a temporally-constrained variant of the main aiming task (400-500 ms) with a cross-hair target that had no specific boundaries. Therein, an accuracy-constrained aiming task was performed with target sizes that were scaled to a proportion of the participants' own distribution of primary movement endpoints (~38%, 68%, 87%, 95%) (for similar procedures, see Carlton, 1994; Hseih et al., 2017; 2019).

In light of the forementioned models, our predictions effectively reconcile or combine the theoretical stances put forth by the *optimized submovement* and *minimization models*. That is, the primary movement endpoints should come nearer the target-centre when performed to a target whose size is more than or equivalent to the effective target width (i.e., ≥95% of the distribution). In this regard, participants should maximize their chances of initially reaching the target without necessarily undertaking any form of time-consuming secondary corrective submovement (Meyer et al., 1988). However, the primary movement endpoints should begin to undershoot the target when its size no longer subtends the effective target width (i.e., <95% of the distribution). In this regard, participants should try to minimize their time and energy-expenditure by assuming a less costly undershoot with a secondary corrective submovement in-mind (Elliott et al., 2004). Taken together, the central tendency may be influenced by the perceived need, or lack thereof, for a secondary corrective submovement – if it is not likely to be needed, then the central tendency will appear near target-centre; but if it is, then the central tendency will begin to undershoot the target.

Method

Participants

A power analysis was conducted using G*Power (version 3.1.9.4; see Faul et al., 2007) with input parameters including $\alpha = 0.05$, $1\text{-}\beta = 0.80$, and $f = 0.57$ (large) (based on the smallest effect size available for primary movement endpoints from a collection of recent related studies; Roberts, 2020; Roberts et al., 2016; Slifkin & Eder, 2017). The minimum estimated sample size was 6 participants. A total of 9 participants (age range = 21-40 years; 7 males, 2 females) provided written informed consent to take part in the study (including the lead author). Participants self-declared as being right-handed, had normal or corrected-to-normal vision, and no known neurological condition. The study was designed and conducted in accordance with the Declaration of Helsinki (2013) and approved by the Liverpool Hope University Research Ethics Committee (ref no.: S 15-06-2017 DEL 013).

Materials and Set-up

Participants sat directly in front and near-centre of a desk-mounted digitizing tablet, which was connected to a computer via a universal serial bus (USB) (GTCO Calcomp Drawing Board VI; temporal resolution = 60 Hz, spatial resolution = 1000 lines per inch). Further in front of the digitizing tablet was a vertically-oriented LCD monitor (47.5 cm × 27.0 cm; temporal resolution = 60 Hz; spatial resolution = 1280 × 800 pixels) that displayed augmented feedback on movement times (see *Session 1 Protocol*). Visual targets were printed on an A4 sheet of paper, which was secured to the active surface of the digitizing tablet by placing it underneath a transparent acrylic sheet that was attached near the top.

Movements were captured by a stylus remotely connected to the digitizing tablet, and retro-reflective markers attached to the same stylus (near the tip, middle and top) and detected via an 8-camera external motion capture system (Vicon Vantage, 16-megapixel resolution, sampling rate = 200 Hz) mounted above and equally spread around the movement environment. The digitizing tablet was primarily intended to provide an adequate aiming surface and generate immediate augmented feedback of the movement time (see *Session 1 Protocol – Baseline Trials),* while the more detailed spatiotemporal characteristics of the movement (i.e., primary movement location) were provided by the external motion capture system. The events linked to the digitizing tablet and screen displays were controlled by Matlab (2018b, The Mathworks Inc., Natick, MA) running Psychtoolbox (version 3.0.11) (Pelli, 1997), and the external motion capture system was independently controlled by the experimenter for each trial.

Session 1 Protocol – Baseline Trials

Participants performed a three-dimensional aiming movement from left-to-right using their dominant right limb on the digitizing tablet. The start and end target positions were marked by two cross-hairs (1 x 1 cm lengths; 2 mm width lines) that were each separated by 243 mm. The movements had to reach as close as possible to the target cross-hair within 400-500 ms, and was thus a temporally-constrained task. This constraint was deemed a reasonable time-window in order to appropriately traverse the amplitude and utilise sensory feedback for late online control when it came to the accuracy-constrained component of the study (see *Session 2 Protocol*) (e.g., Elliott et al., 2014; Gottwald et al., 2020; Heath et al., 2011; Khan et al., 2003; Mendoza et al., 2006).

Participants would signal that they were ready to start a trial by using the stylus to make contact with the digitizing tablet and press down on the tip. Following a 2-s delay, a

100-ms tone (750 Hz) was generated to signal the start of the trial and allow participants to freely initiate their movement. The start and end of the movement was marked by the initial release and final press of the stylus tip. Therein, augmented feedback of the movement time was displayed as text on the adjacent screen. Participants were instructed to observe their movement time from the previous trial before progressing onto the next attempt by pressing any key on a keyboard. If the movement time was within the criterion time-window (400-500 ms), then the text would appear in white and participants could freely move onto the next trial. If the movement was too fast (<400 ms) or slow (>500 ms), then the text would appear in red and participants would have to repeat the trial. There was a requirement of 30 successful baseline trials to-be-completed before the end of the session with the first 10 trials regarded as practice (~25 mins).

Session 2 Protocol – Accuracy-Constrained Trials

The second session was completed 3-7 days after the first session with baseline trials (see Table 1). It was completed within 3 hours of the original time in order to avoid any time-of-day effects (Gueugneau et al., 2017; Gueugneau & Papaxanthis, 2010). Participants performed the same three-dimensional aiming movement from left-to-right using their dominant right limb. However, the end target position was now a circular target whose size was scaled according to the spatial variability from the baseline trials. That is, the target size represented near 38.30% (x1 SD; +/-0.5), 68.26% (x2 SD; +/-1.0), 86.64% (x3 SD; +/-1.5) and 95.44% (x4 SD; +/-2.0) of the distribution of primary movement locations at baseline (see *Data Management and Analysis*). The movement had to be performed as quickly and accurately as possible, and was thus regarded as an accuracy-constrained task.

Participants followed the same procedure as Session 1 in order to commence a trial and issue a movement. However, the augmented feedback on movement time was no longer provided, and thus there was no longer the possibility to repeat trials based on a previously executed movement time. There were 30 trials for each target condition with the first 10 trials regarded as practice. Target conditions were presented as blocks with their order being randomized across participants courtesy of a Latin Square design. Before and after each block of trials, there were 2 separate recordings to mark the start (cross-hair centre) and end target (near edge of the circle) positions for the purposes of calibrating the external motion capture system with respect to the movement environment.

Data Management and Analysis

Three-dimensional position-time series data from the external motion capture system were processed using a Butterworth filter (2^{nd}-order, 10 Hz low-pass cut-off, dual-pass). Data were differentiated to obtain velocity (single), acceleration (double), and jerk (triple). Movement onset was defined as the first moment that the velocity reached >20 mm/s and continued for at least a 40-ms time-window (8 samples). Movement offset was defined as the first moment that the velocity reached between <20 mm/s and >-20 mm/s, and remained so for the same 40-ms time-window.

A search for two-component submovements was conducted using standard criteria: (i) positive-to-negative zero-crossing in velocity (type 1; reversal); (ii) negative-to-positive zero-crossing in acceleration following peak deceleration (type 2; re-acceleration); (iii) positive-to-negative zero-crossing in jerk following peak deceleration (type 3; discontinuities) (Elliott et al., 2014; Fradet et al., 2008b). In order to register as a two-component submovement, one of these criteria had to maintain a duration of at least 40 ms. If a combination of these criteria were present within a single trial, then the earliest event was taken to reflect the end of the primary movement.

In order to appropriately scale the target size for accuracy-constrained trials (Session 2), we multiplied the spatial variability (i.e., standard deviation) of the resultant location ($\sqrt{x^2+y^2}$; x- and y-axes represented the primary and secondary directions, respectively) at the primary movement from the baseline trials (Session 1) by a factor of 1, 2, 3 and 4 (for similar procedures, see Carlton, 1994). These scaling factors equated to a 38.30%, 68.26%, 86.64% and 95.44% of the distribution of locations at the primary movement, respectively (see Welford, 1968).

In line with the hypotheses surrounding the central tendency of the movement amplitude, the primary direction of the movement (x-axis) was isolated for further analysis. Specifically, we calculated the mean and spatial variability of the primary movement displacement prior to a possible secondary submovement. In the event that there was no secondary submovement, the primary and terminal movement endpoints were coincident with one another. In addition, we calculated the constant error (CE) and variable error (VE) by taking the mean and population standard deviation of the difference between the total movement amplitude and required target amplitude (based on the grand mean from a series of calibrations of the start and end target positions).

Dependent measures were statistically analysed using a one-way repeated-measures Analysis of Variance (ANOVA) featuring the factor of target (x1-4). In the event of a violation in the assumption of Sphericity (courtesy of Mauchly's test), then the Huynh-Feldt corrected value was adopted providing Epsilon was >.75. If otherwise, then the Greenhouse-Geisser corrected value was adopted (original degrees-of-freedom were reported). Partial eta-squared (η^2) was used as a measure of effect size. Statistically significant effects were further detailed using polynomial contrasts or trend analyses.

Results

Primary and Terminal Analysis

The mean movement time from baseline (Session 1) was 438.13 ms (*SE* = 7.59). Table 1 shows the allocated target sizes for the accuracy-constrained data collection (Session 2) after they were scaled according to the original effective location of the primary movement. The mean allocated target sizes in ascending order of the scaling factors (x1-4) could be rounded to 3, 6, 9, and 12 mm.

[Insert Table 1 about here]

Within the accuracy-constrained trials (Session 2), there was no significant main effect of target for mean displacement (*grand M* = 245.44 mm, *SE* = 1.23), $F(3, 24) = .92$, $p > .05$, *partial* $\eta^2 = .10$, nor spatial variability (*grand M* = 5.80 mm, *SE* = .35), $F(3, 24) = .11$, $p > .05$, *partial* $\eta^2 = .01$, at the primary movement endpoint (see Figure 2A).[1] In a similar vein, there was no significant main effect of target for CE (*grand M* = .64 mm, *SE* = .59), $F(3, 24) = .40$, $p > .05$, *partial* $\eta^2 = .05$, nor VE (*grand M* = 2.87 mm, *SE* = .25), $F(3, 24) = 2.18$, $p > .05$, *partial* $\eta^2 = .05$, at the terminal movement endpoint (see Figure 2B).

Further inspection of Figure 2 suggests that there was less of a tendency for the primary movement to reach under (i.e., undershoot) compared to the centre of the target. To further explore this observation, we calculated the difference between the mean displacement at the primary movement and near edge of the target boundary, as well as the difference between this displacement and centre of the target (i.e., negative scores representing an undershoot; positive scores representing a longer amplitude). If there was less of a tendency to undershoot the near target boundary in favour of the target-centre, then we would observe a higher and more positive score for the difference with respect to the near target boundary, while the score would be near zero when the difference is made with respect to the target-centre. A series of single-sample t-tests (comparing to a theoretical value of zero) revealed a significantly longer displacement of the primary movement than the near target boundary for each of the target conditions (*grand* M = 5.91 mm, SE = 1.17) ($ts(9)$ = 2.52-5.57, $ps < .05$, ds = .84-1.86), although there was no such significant difference between this same displacement and target-centre (*grand* M = 2.17 mm, SE = 1.23) ($ts(9)$ = 1.26-2.10, $ps > .05$, ds = .42-.70).

Moreover, inspection of Figure 2 would suggest that there was some error or discrepancy between the W_e and nominal target size–also known as target utility. Thus, we calculated an index of target utility (I_u) using the following formula: $\log_2(W_e / W)$ (W representing the nominal target width) (Zhai et al., 2004). In this regard, a positive score earmarks over-utilization (i.e., missing of the target), while a negative score earmarks under-utilization (i.e., concentrated well within the target). There was a significant main effect of target, $F(3, 24) = 69.38$, $p < .001$, *partial* $\eta^2 = .90$, which indicated a significant linear ($p < .001$) and quadratic ($p < .01$) component. This outcome translates as an over-utility for the proportionally smaller target, but near perfect utility for the proportionally larger target that was roughly equivalent to the W_e from Session 1 (x1 M = 1.81, SE = .15; x2 M = .94, SE = .13; x3 M = .45, SE = .12; x4 M = .11, SE = .13).[2]

Because of these discrepancies, combined with the modest variability that was evidenced at the primary movement endpoint, it raises the issue of whether any of the secondary submovements were in fact functionally linked to a correction within the trajectory. Consequently, we analysed spatial variability between the primary submovement and terminal movement endpoints for only those trials comprising two-component submovements, where the primary submovement was followed by a secondary submovement before finally reaching the terminal movement endpoint. That is, we incorporated an additional factor to form a two-way repeated-measures ANOVA featuring factors of target (x1-4) and kinematic landmark (primary, terminal). There was no significant main effect of target, $F(3, 24) = .25$, $p > .05$, *partial* $\eta^2 = .03$, although there was a significant main effect of kinematic landmark, $F(1, 8) = 32.50$, $p < .001$, *partial* $\eta^2 = .80$, where there was a marked decrease between the primary submovement and terminal movement endpoints. There was no significant interaction between target and kinematic landmark, $F(3, 24) = .30$, $p > .05$, *partial* $\eta^2 = .04$. While indifferent to an influence of target size, it appears at least some of the secondary submovements were associated with corrective processes.

For MT, there was a significant main effect of target, $F(3, 24) = 3.95$, $p < .05$, *partial* $\eta^2 = .33$, which indicated a significant linear component ($p < .05$). This finding was corroborated by a significant positive relation between the mean movement time and nominal Index of Difficulty (ID) (i.e., $\log_2(2A / W)$, where A represents the target amplitude and W represents the target width); thus complying with Fitts' Law (Fitts, 1954) (see Figure 3A).

Perhaps surprising was the absence of a statistically significant effect for variability when we consider the differences in movement time. However, a follow-up analysis indicated a significant positive relation between the effective target width (W_e) (i.e., SD x 4.133; Welford, 1968) and average velocity (i.e., A / MT; movement amplitude divided by the total movement time); thus complying with Schmidt's Law (Schmidt et al., 1979) (see Figure 3B).

[Insert Figure 2 and 3 about here]

Supplementary Kinematic Analysis

Because of the relatively limited modulation of the central tendency according to the different targets, it is of interest to examine how individuals navigated through the entire trajectory. That is, it is possible that the earlier portions of the trajectory were influenced by the scaled target sizes. For example, the displacement at peak deceleration–comprising the initial impulse phase–has also been known to demonstrate an undershoot-like tendency, which is symptomatic of energy-minimization (Roberts et al., 2016; Roberts & Grierson, 2020). With this in mind, we analysed the magnitude, time and displacement of kinematic landmarks, including peak acceleration, peak velocity and peak deceleration, using the same statistical analysis of a one-way repeated-measures ANOVA.

There was a significant main effect of target for the magnitude of peak acceleration, $F(3, 24) = 4.31$, $p < .05$, *partial* $\eta^2 = .35$, peak velocity, $F(3, 24) = 4.51$, $p < .05$, *partial* $\eta^2 = .36$, and peak deceleration, $F(3, 24) = 4.41$, $p < .05$, *partial* $\eta^2 = .36$. These effects indicated a significant linear component involving a relation between magnitude and target size that was positive for peak acceleration and peak velocity, and negative for peak deceleration (*ps* < .05).

Meanwhile, there was no significant main effect of target for the time to peak acceleration, $F(3, 24) = .95$, $p > .05$, *partial* $\eta^2 = .11$. However, there was a significant effect for the time to peak velocity, $F(3, 24) = 3.84$, $p < .05$, *partial* $\eta^2 = .33$, and peak deceleration, $F(3, 24) = 4.44$, $p < .05$, *partial* $\eta^2 = .36$, which each recognised a significant linear component that was consistent with the inverse relation between total movement time and target size (*ps* < .05) (see Figure 4).

Finally, there was a significant main effect of target for the displacement at peak acceleration, $F(3, 24) = 6.75$, $p < .01$, *partial* $\eta^2 = .46$, which indicated significant linear ($p < .01$) and quadratic ($p < .05$) components highlighting an initial increase in displacement as a function of target size that eventually reached an asymptote. However, there was no significant main effect of target for the displacement at peak velocity, $F(3, 24) = .14$, $p > .05$, *partial* $\eta^2 = .03$, nor peak deceleration, $F(3, 24) = .39$, $p > .05$, *partial* $\eta^2 = .05$.

[Insert Figure 4 about here]

Discussion

The present study examined two influential models of movement optimization surrounding the speed-accuracy trade-off within manual aiming. Firstly, there is the *optimized submovement model* (Meyer et al., 1988) that predicts a modulation in limb velocity in order to achieve the shortest possible movement time without inadvertently increasing the signal-dependent noise, while the primary movement endpoints tend to reach near target-centre so as to maximize the chances of hitting the target. Alternatively, the *minimization model* (Elliott et al., 2004) predicts modulation of the limb location, where the pre-programming of the primary movement accommodates later online control by initially undershooting the target so as to minimize the time and energy-expenditure of the subsequent secondary corrective submovement.

With this in mind, we attempted to exploit the common assumption that the central tendency of primary movement endpoints is contingent upon the relation between spatial variability and target size. That is, we had target sizes scaled according to the participants' own inherent variability, which was directly adapted from the spatial variability of the primary movement endpoint at baseline (Session 1). In line with the tenets of both models, it was predicted that a tendency toward target-centre would emerge when the nominal target width subtends the effective target width (i.e., 95% of the distribution; x4 SD), although this tendency may shift toward undershooting once the nominal target width was exceeded by the effective target width (i.e., <95% of the distribution; x1-3 SD).

The findings revealed that the primary movement endpoints were closer to target-centre than they were to the near target boundary irrespective of target size. Meanwhile, there was a negative linear relation between movement time and target size. More precisely, the movement kinematics revealed an increase in the magnitude of each kinematic event when there was an increase in target size. Moreover, aiming movements appeared to reach the initial peak acceleration at a similar point in time across each of the targets, but with an increase in its displacement when there was an increase in target size. Thereafter, peak velocity and peak deceleration were reached within shorter times following increases in target size, but at similar spatial locations across each of the targets. These findings are more closely aligned with the pattern of aiming described by the *optimized submovement model* (Meyer et al., 1988; see also, Slifkin & Eder, 2017; Zelaznik, 2018). That is, participants appeared to increase the chances of hitting the target by tending to end the primary movement near-centre, while parameterizing the force output within their initial impulse in order to avoid signal-dependent noise causing an error (Schmidt et al., 1979). This approach contrasts with the reported tendency to undershoot the target with a view to minimizing the time and energy-expenditure of a secondary corrective submovement as it avoids having to overcome inertia and switch the agonist and antagonist muscle functions in the event of an overshoot (Elliott et al., 2004; see also, Engelbrecht et al., 2003).[3]

Consequently, we may re-evaluate the precise context that led to the original formulation of the *minimization model*. Of interest, the study from Elliott et al. (2004) featured a pay-off structure that granted a disproportionate monetary punishment for any misses ($0.60) relative to a reward for any improvement (decrease) in movement times (max. $0.40) (for a similar procedure, see Oliveira et al., 2005). The influence of such a pay-off may be best highlighted by the notion of maximum expected gain (Trommershäuser et al., 2003a, b), which suggests performers generally converge onto a motor strategy that maximizes (minimizes) gains (losses). Among the cost functions that comprise this model include the noise that makes the outcome uncertain, as well as the consequences of potential outcomes (i.e., reward success vs. punish error). For example, when freely able to select movements toward a rewarding target area (e.g., +100 points) alongside a punishing penalty area (e.g., -100 points) within a particular time-frame (e.g., <750 ms), performers generally move closer toward the target boundary and further away from the penalty area (and target-centre) when there is either increased spatial variability, reduced proximity between the target and penalty areas, and/or increased punishment (e.g., -100 vs. -500 points) (see also, Neyedli & Welsh, 2013; Trommershäuser et al., 2005). Thus, we may envisage a similar “penalty area” within Elliott et al. (2004), which surrounds the entire vicinity of the target owing to the punishment imposed on any misses. As a result, the noise that causes uncertainty may have promoted a motor strategy that primarily combats the potential for error, and subsequently avoids punishment. This strategy appeared to involve the programming of a primary movement that could accommodate a secondary corrective submovement, which effectively utilises online sensory feedback in order to reduce the uncertainty and secure a target hit.

At this juncture, owing to the minimization of time and energy-expenditure, the correction being accommodated for is deemed best to come from an undershoot rather than an overshoot. Consistent with this logic is evidence from studies that have either reversed (Oliveira et al., 2005) or exacerbated (Lyons et al., 2006) the proposed energy-expenditure of undershooting compared to overshooting. In the former instance, an assistive elastic band that was attached to a manipulandum caused the limb to be propelled toward the target resulting in greater overshooting because it avoids the energy-expenditure that would be required to dampen the velocity and clamp the limb (Oliveira et al., 2005). In the latter instance, aiming downward within the vertical axis caused even greater undershooting than normal because it avoids the cost of reversing the limb against gravitational forces (Lyons et al., 2006; see also, Burkitt et al., 2017; Elliott et al., 2014; Roberts, 2020; Roberts et al., 2016). Within the context of the present study, the failure to capture this minimization may be at least partially attributed to the absence of a penalty. Instead, performers may have increased their chances of hitting the target with the primary movement by having their tendency located near centre, while the tail-ends of the distribution can more readily afford to miss the target because it does not incur a loss. Thus, by definition, it is possible that imposing a penalty may begin to elicit a tendency that initially undershoots the target when its size becomes smaller than the area of uncertainty (i.e., <95% of the distribution/x1-3 SD).

When considering the similarities in the tendency of primary movement endpoints across each of the targets, it appears there was a uniform approach that meant very few forms of motor strategy were adopted. Consequently, it led to an over-utility of the smaller targets and near perfect utility of the larger target that equated to participants' effective target width (see also Zhai et al., 2004). This uniform approach was perhaps accommodated by the invariant task parameters including set amplitude and target location (N.B., while different target images were implemented between the blocks, they were placed in the same area of the aiming surface). Such parameters are particularly relevant when we consider the contribution of egocentric (body-centred) reference codes toward visuomotor control (Neely et al., 2008; Westwood & Goodale, 2003; see also, Glover, 2004).

Despite the previously stated importance of a motor strategy that is sensitive to context (Trommershäuser et al., 2003a, b; see also, Hamilton & Wolpert, 2002; Vetter & Wolpert, 2000), it is also worthwhile considering the potential cost associated with cognitive factors or the utility of resources that are required to pre-programme aiming movements across a series of trials. Along these lines, it was recently shown that younger adults tend to adopt a smaller number of submovement strategies and prefer to opt for a "one-shot" approach to the target (i.e., single component movement) (Poletti et al., 2015; 2016). In a similar vein, the spatiotemporal characteristics of pre-programmed movements from previous attempts (trial *n*-1) have been known to contaminate movements on subsequent attempts (trial *n*) despite there being clear differences in the task parameters (e.g., no obstacle/obstacle: Griffiths & Tipper, 2009; 2012; Jax & Rosenbaum, 2007; low/high ID: Tang et al., 2018).

Thus, in addition to the cost or consequences of movement outcomes, it may be important to more overtly manipulate task parameters (e.g., 5-80 mm target; Slifkin & Eder, 2017), and with that, the perceived need to vary motor strategies and update the pre-programming of aiming movements.

What's more, the present study showed a marked decline in spatial variability between the primary and terminal movement endpoints, which would suggest at least some corrective function of the secondary submovement (Woodworth, 1899; see also, Elliott et al., 2001). Indeed, in order for the initial increases in spatial variability to be overturned and converge onto the target, then there must be some intervening correction courtesy of online sensory feedback (Khan et al., 2003; Khan et al., 2006). That said, there is the possibility that some submovements may result from a biomechanical artefact including the stabilization of the limb during movement termination (Dounskaia et al., 2005; Fradet et al., 2008a; Hsieh et al., 2017). Future research may wish to more clearly distinguish the neuromechanical sources contributing to submovement structure in order to more appropriately inform emerging theoretical models of manual aiming.

In conclusion, the present study adapted the influence of inherent variability with respect to the target by alternatively using this variability to scale the size of the targets. Participants tended to aim their primary movements closer to target-centre and modulated the limb velocity to limit the error induced by noise. These findings reveal that aiming movements may more closely resemble the tenets of the *optimized submovement model* when under typical constraints, where studies may simply instruct performers to accurately reach the target as quickly as possible over a single course of trials (e.g., <300 trials or single lab visit). However, the potential influence of other factors, including the external gains or losses associated with pay-offs, may manifest in aiming movements that more closely reflect the time and energy-minimization following an undershoot. In this regard, it is of interest to explore the unique parameters that may manifest in a switch between a probabilistic to "play-it-safe" strategy.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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Footnotes

1) The grand mean proportion of trials featuring two-component submovements was 65.26% (*SE* = 7.48). Further inspection of these particular trials once more revealed no significant main effect of target for the mean displacement (*grand M* = 245.68 mm, *SE* = 1.35), $F(3, 24) = 1.28$, $p > .05$, *partial* $\eta^2 = .14$, nor spatial variability (*grand M* = 6.64 mm, *SE* = .53), $F(3, 24) = .11$, $p > .05$, *partial* $\eta^2 = .01$, at the primary submovement.

2) Consistent with target utility, the mean target hit rates were comparatively low for the smallest possible target (x1 *M* = 71.36%, *SE* = 6.92) compared to the other targets (x2 *M* = 82.83%, *SE* = 6.89; x3 *M* = 85.53%, *SE* = 5.73; x4 *M* = 94.75%, *SE* = 2.95). This outcome may be attributed to the assignment of an excessively small or miniscule nominal target width (see Table 1), which could more likely incur an error through slight physiological tremor (Lakie et al., 2012) even after a potentially low-impulse movement and/or following a secondary corrective submovement (Elliott et al., 2001).

3) An additional feature that could discriminate previous findings in support of the *optimized submovement* and *minimization models* is the underlying aiming task characteristics. For example, the original study from Meyer et al. (1988) featured a one-dimensional wrist rotation, while Elliott et al. (2004) involved three-dimensional upper-limb coordination (i.e., shoulder-elbow-wrist). Furthermore, Elliott et al. (2004) adopted an aiming movement along the mid-sagittal plane (i.e., anterior-posterior), while the present study moves along the frontal plane (i.e., abduction-adduction). While there are perhaps differences in the underlying dynamics and biomechanical costs (e.g., Soechting et al., 1995), such constraints do not necessarily relate to the model predictions unless they indirectly influence the variability and secondary corrective submovement.

Figure captions

Figure 1. Hypothesized frequency distributions of primary movement endpoints in the primary direction of the movement. Target areas are represented by the superimposed grey blocks. Upper panels indicate the hypothesized effects for smaller (A) and larger (B) targets according to the *optimized submovement model* (Meyer et al., 1988). Lower panels indicate the hypothesized effects for smaller (C) and larger (D) targets according to the *minimization model* (Elliott et al., 2004).

Figure 2. Mean displacement at the primary movement (A) and terminal endpoint (B) as a function of the scaled target size conditions. Error bars represent the within-participant standard deviation. Emboldened upper and lower markers indicate the mean allocated target boundaries for each scaling factor. Dotted line indicates the amplitude to target-centre.

Figure 3. Illustration of the relation between mean MT and ID (A), and mean W_e and average velocity (B).

Figure 4. Mean displacement at kinematic landmarks across time. Symbols represented within the legend indicate the scaled target size conditions.

Tables

Table 1. Target sizes (mm) allocated to individual participants that were scaled according to their original spatial variability. Note, the scaled factor of 4 nears the effective target width (W_e).

	Test-Retest Interval (Sessions)	**x1 (38.30%)**	**x2 (68.26%)**	**x3 (86.64%)**	**x4 (95.44%)**
P1	7	4.78	9.56	14.35	19.13
P2	7	3.60	7.21	10.81	14.42
P3	4	2.43	4.86	7.29	9.71
P4	3	3.47	6.93	10.40	13.87
P5	5	2.54	5.07	7.61	10.15
P6	5	2.47	4.94	7.41	9.88
P7	5	3.25	6.49	9.74	12.99
P8	7	2.32	4.63	6.95	9.26
P9	7	2.10	4.20	6.29	8.39
Mean (±SE)	5.56 (0.50)	2.99 (0.29)	5.99 (0.57)	8.98 (0.86)	11.98 (1.15)