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 Frequency Distributions of Target-Directed Movements: Examining Spatial Variability in Its Wider Context

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Abstract

Investigations of visually-guided target-directed movement frequently adopt measures of within-participant spatial variability to infer the contribution of planning and control. The present study aims to verify this current trend by exploring the distribution of displacements at kinematic landmarks with a view to understanding the potential sources of variability. Separate sets of participants aiming under full visual feedback conditions revealed a comparatively normal distribution for the displacements at peak velocity and movement end. However, there was demonstrable positive skew in the displacement at peak acceleration and a significant negative skew at peak deceleration. The ranges of the distributions as defined by either $\pm 1SD$ or $\pm 34.13^{th}$ percentile (equivalent to an estimated 68.26% of responses) also revealed differences at peak deceleration. These findings indicate that spatial variability in the acceleration domain features highly informative systematic, as well as merely inherent, sources of variability. Implications for the further quantification of trial-by-trial behaviour are discussed.

Introduction

Since the findings of endpoint variability in target-directed movements being scaled to the magnitude of response impulses (Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979), eminent theories have placed a great emphasis on how it is performers cope with such circumstances and the associated trade-off between speed and accuracy (Fitts, 1954; Fitts & Peterson, 1964). Namely, Meyer and colleagues (Meyer, Abrams, Kornblum, Wright, & Smith, 1988) suggested primary movement endpoints assume a central tendency on or over the target centre so that the majority of aims can subtend the target boundaries. In the event of an initial error (synonymous with the tails of the endpoint distribution), the performer may issue a secondary corrective movement to eventually reach the target. Alternatively, it has been argued that while a normal distribution in the primary movement endpoints may manifest, these movements tend to fall short of the target location (undershoot) so as to avoid a potential cost of moving beyond the target (overshoot) (Elliott, Hansen, Mendoza, & Tremblay, 2004). This 'cost' is reflected by the need of the performer to overcome inertia and switch the agonist-antagonist arrangement in order to reverse the limb's location. However, when the endpoint variability begins to decline, and presumably subtend the target boundaries, the performer may begin to undershoot less and effectively 'creep-up' on the target. This notion draws heavily on the findings that primary movement endpoints are heavily related to their frequency distribution (i.e., spatial variability) (see Lyons, Hansen, Hurding, & Elliott, 2006; Worringham, 1991).

Alongside these suggestions, traditional views of target-directed movement contend that there are two sensorimotor components: early ballistic phase associated with pre-movement planning (*initial impulse*) and late 'homing-in' phase associated with the use of online sensory feedback for the amendment of errors (*current control*) (Elliott, Helsen, & Chua, 2001; Meyer et al., 1988; Woodworth, 1899). The very first instance of these so-called

components was reflected by a series of delayed discontinuities when aiming with a pencil between two targets on a rotating drum; so-long as there was an opportunity to use visual feedback within the movement (Woodworth, 1899). Following the advent of motion capture systems, there was an exciting possibility of more precisely corroborating Woodworth's early findings by measuring the primary and secondary submovement components between different feedback conditions (vision vs. no vision). However, despite the obvious advantages in endpoint accuracy for vision compared to no vision conditions, there was no such difference in the nature or number of secondary submovements (e.g., Elliott, Carson, Goodman, & Chua, 1991).

Herein, the measures of endpoint dispersion that were previously mentioned were adapted for the assessment of within-participant standard deviation of earlier locations of the trajectory (see Khan et al. (2006) and Hansen, Elliott, & Khan (2008)); also referred to as *spatial variability*. That is, in order for the increasing variability that is observed during the earlier portions of the movement to be overturned and accurately subtend the target, there must be some intervening control process that is contingent upon the use of online sensory feedback. Indeed, there has been much evidence to support this conjecture following larger declines in spatial variability toward the end of the movement when performers are presented with vision compared to no vision (e.g., Khan et al., 2003; Khan, Elliott, Coull, Chua, & Lyons, 2002). At the same time, there has been evidence to suggest performers can reduce the spatial variability at earlier landmarks to reflect a more refined specification of efferent signals (e.g. Allsop, Lawrence, Gray, & Khan, 2016; Hansen, Tremblay, & Elliott, 2005; Roberts, Wilson, Skultety, & Lyons, 2018). As a result, these measures have been heavily leveraged to substantiate two-component views of target-directed movement, and potentially steer researchers to a greater consideration of dispersion rather than tendency.

While the organisation and manifestation of submovement components based on endpoint variability is robust (Elliott et al., 2004; Worringham, 1991), it remains to be seen whether the same assumption of a normal trend in the response distribution unfolds at earlier kinematic landmarks (peak acceleration, peak velocity, peak deceleration). Indeed, implicit within the proposed value served by spatial variability is the notion that we may correspondingly determine the effective limb location at various points within the trajectory (see Welford, 1968) – location of the limb that most likely subtends a select proportion of the responses (e.g., 34.13% = 1SD). For this inference to be so, the error that is incurred prior to 'homing-in' should be somewhat random or stochastic in nature and reflect a normal distribution. However, it is also possible that the changes reported in spatial variability across kinematic landmarks may reflect a systematic alteration or planning error (van Beers, 2009). In other words, the current reference to spatial variability may not be fully indicative of limiting the negative effects of 'noise' through the refined parameterization and control of movement, but mere adaptation or exploratory behaviour (*cf.* Faisal, Selen, & Wolpert, 2008; van Beers, Haggard, & Wolpert, 2004). Afterall, there needs to be some degree of variability if performers are to learn in a novel sensorimotor environment over a series of trials (e.g., Shea & Morgan, 1979).

To this end, the following study aims to examine these issues, and whether it is premature to conceive of early spatial variability as a marked reflection of performers' response distribution. With this in mind, the present study may offer further insights into the inferences associated with spatial variability and identify precise indicators of trial-by-trial behaviour. Thus, previously collected data sets from our lab pertaining to typical controlled circumstances of rapid aiming with visual feedback were adopted (see Roberts, Elliott, Lyons, Hayes, & Bennett, 2016; Roberts et al., 2018). The purpose of conducting this analysis across multiple data sets is to vouch for the repeatability of the findings within

separate sets of participants. Providing the changes in spatial variability across the trajectory are the result of 'random effects' such as neuromotor noise, then we would anticipate a normal distribution of limb locations. Alternatively, a systematic alteration to the intended strategy or an error in planning for some of the movement attempts may be indicated by a degree of skewness. That is, variation in the trial-by-trial behaviour predominantly resulting from the performer actively adjusting the efferent output.

Method

Participants

Eleven participants were eligible to participate from the first study, and sixteen participants from the second study (age range = 18-30 years). All participants signed an informed consent form, and were self-declared right-handed, had normal or corrected-to-normal vision and free of any neurological condition. These studies were designed and conducted in accordance with the Declaration of Helsinki, and approved by the local ethics committee.

Apparatus, Task and Procedure

With regards the first data collection, stimuli were presented on a horizontally mounted monitor (66-cm diagonal; temporal resolution = 60 Hz; spatial resolution = 1024 x 768 pixels). The experiment was controlled via a custom written program in E-prime (Psychology Software Tools Inc., Sharpsburg, PA). The home position was located in front of the participants who had to rest their right index finger on it prior to the start of the trial. Following a random foreperiod (800-2800 ms), a 1-cm diameter target would appear 24 cm along the participant midline. Herein, participants had to aim as quickly and accurately as possible by moving their right limb along the horizontal mid-sagittal axis (forward).

Movements were captured courtesy of an infra-red marker that was attached to the right index finger and detected using an Optotrak 3020 system (Northern Digital Instruments, Waterloo, ON) recording at 200 Hz. These movements were executed under normal/low and high state anxiety situations, although we were only concerned with the normal/low anxiety set for which there were 30 trials. Participants were granted an initial 30 familiarisation/practice trials in advance of the experiment.

In a similar vein, the second set of data featured stimuli that were presented on a wall-mounted monitor (54-cm diagonal; temporal resolution = 85 Hz; spatial resolution = 1600 x 1200 pixels). The experiment was controlled by a custom-written program in Matlab (The Mathworks Inc., Natick, MA). The trial proceedings and task objectives were precisely the same as above, only stimuli and movements were made for a 16-cm amplitude along the mid-line of the body within the vertical extent (upward). These movements were executed amongst a series of potential other movement trials (short and long amplitude, single- and two-segment movements, up and down directions), although the current focus is adopted for the sake of brevity and without conflating the principle objective of this study. There were 20 movement trials in the present study condition.

Data Processing and Analysis

Position data were filtered using a second-order, dual-pass Butterworth filter with a 10 Hz low-pass cut-off frequency. Data were differentiated and double-differentiated to obtain velocity and acceleration, respectively. Movement onset and offset were respectively defined as the moment velocity within the primary movement direction reached above and below 10 mm/s for 40 ms or more (>8 frames).

Displacement data at each kinematic landmark were extracted including, peak acceleration (PA), peak velocity (PV), peak deceleration (PD) and movement end (END). In

order to quantify violations in the normality of the within-participant response distribution, the degree of skewness was calculated by converting displacement data into z^3 scores. By taking the third moment, the z-scores were accentuated while retaining the direction with respect to the participant mean (i.e., position/negative). In addition, the difference between +1SD and -1SD of the within-participant mean position at kinematic landmarks was calculated (standard deviation range) for comparison with the difference between 84.13[th] and 15.87[th] percentiles (median $\pm$ 34.13%) (percentile range). These ranges were selected as they theoretically equate to 68.26% of the response distribution (-1SD = 15.87%, +1SD = 84.13%). Thus, a normal distribution that positively reflects the effective limb position should indicate an overlap between the ranges, although a violation should unveil differences between the two.

Movement trials featuring reaction times <100 ms or >1000 ms were considered anticipatory or non-reactive responses respectively, and removed from the analysis. In addition, movement times exceeding >800 ms were considered non-rapid target responses, and also removed prior to analysis. For the analysis of mean z^3 scores, a one-way repeated-measures ANOVA (4 levels of kinematic landmark; PA, PV, PD, END) was initially conducted. In order to examine the extent of skewness, the mean z^3 scores were compared with a theoretical value of 0 (representing mean displacement) using single-sample t-tests. Finally, for the analysis of ranges encompassing the response distribution, a 2 statistic (standard deviation, percentile) x 4 kinematic landmark (PA, PV, PD, END) repeated-measures ANOVA was conducted. Mauchly's test of Sphericity was used to assess the variability of differences. In the event of a violation, the Huynh-Feldt value was adopted when epsilon was >.75, although the Greehouse-Geisser value was adopted if otherwise (original Sphericity-assumed degrees-of-freedom are reported). Partial eta-squared (η^2) was used as an effect size measure, and any significant effects featuring more than two levels

were decomposed using Tukey HSD post hoc procedure. Significance was declared at $p <$ .05.

Results

Horizontal/Forward Movements

As a general account of the target-directed aims, the means of reaction time, movement time and constant error were 363.57 ms (SD = 45.44), 466.75 ms (SD = 52.35) and -.53 mm (SD = .70), respectively. Thus, response distributions (see Figure 1), there was a notable positive and negative skew in peak acceleration and peak deceleration, respectively. However, the displacements at peak velocity and movement end reflected a comparatively normal distribution. Indeed, the one-way ANOVA on z^3 scores revealed a significant main effect of kinematic landmark, $F(3, 30) = 7.77$, $p < .05$, *partial η^2* = .44, which indicated significantly more positive skew for the displacement at peak acceleration compared to peak velocity and peak deceleration ($ps < .05$). In addition, there was a significant difference between the skewness at peak acceleration (M = .79, SD = .79), $t(10) = 3.32$, $p = .01$, and peak deceleration (M = -.78, SD = .99), $t(10) = 2.63$, $p = .03$, compared to 0 (mean score). However, there was no significant difference observed for the displacements at peak velocity (M = -.17, SD = .95), $t(10) = .59$, $p = .57$, and movement end (M = .05, SD = .34), $t(10) = .57$, $p = .58$.

Meanwhile, the factorial ANOVA on the ranges of the within-participant distributions revealed a significant main effect of statistic, $F(1, 10) = 2.28$, $p < .05$, *partial η^2* = .19, as well as kinematic landmark, $F(3, 30) = 32.69$, $p < .05$, *partial η^2* = .77. In addition, there was a significant statistic x kinematic landmark interaction, $F(3, 30) = 32.42$, $p < .05$, *partial η^2* = .23 (see Figure 2 and Table 1). Post hoc analysis revealed a larger range for the within-

participant standard deviation compared to the percentile statistic at peak deceleration ($p <$ .05).[1]

[Insert Figure 1, Figure 2

and Table 1 about here]

Vertical/Upward Movements

To corroborate the findings from our first set of data, the second data reflected target-directed movements with a mean reaction time, movement time and constant error of 300.37 ms (SD = 23.84), 447.08 ms (SD = 43.45) and -.13 mm (SD = 2.43), respectively.

Once more, the within-participant response distributions reflected a degree of skewness in the acceleration domain; namely, at peak deceleration (see Figure 3). The one-way ANOVA revealed a significant main effect of kinematic landmark, $F(3, 45) = 8.55$, $p <$ .05, *partial η^2* = .36, which indicated a significantly greater negative skew for displacement at peak deceleration compared to peak acceleration and peak velocity (*ps* < .05). The single-sample t-test also confirmed a significant negative skew for the displacement at peak deceleration compared to a theoretical value of 0 (mean score) (M = -.81, SD = .68), $t(15)$ = 4.80, p = .00, although there was no significant difference for peak acceleration (M = .32, *SD* = .94), $t(15)$ = 1.37, p = .19, peak velocity (M = .28, *SD* = .67), $t(15)$ = 1.67, p = .12, and movement end (M = -.15, SD = .42), $t(15)$ = 1.40, p = .18.

Meanwhile, the factorial ANOVA revealed a significant main effect of statistic, $F(1, 15)$ = 814.06, $p <$ .05, *partial η^2* = .48, which indicated a larger range between standard deviations compared to percentile scores (see Figure 4 and Table 2). In addition, there was a significant main effect of kinematic landmark, $F(3, 45)$ = 60.50, $p <$ .05, *partial η^2* = .80,

although no significant statistic x kinematic landmark interaction, $F(3, 45) = 1.69$, $p > .05$, *partial* $\eta^2 = .10$.[2]

[Insert Figure 3, Figure 4

and Table 2 about here]

Discussion

Theoretical propositions surrounding target-directed movement contend that there is a normal distribution of endpoint responses, where variations from the mean are the result of stochastic properties (Elliott et al., 2004; Meyer et al., 1988). The present study adapted two sets of data in order to examine the trial-by-trial distribution of limb locations and the associated descriptors at early and late phases of movement. The results indicated a degree of skewness within the acceleration domain. That is, there was some evidence of a positive skew at peak acceleration, although the evidence predominantly pointed to a negative skew at peak deceleration. These violations in normality were corroborated by a limited overlap between the parametric (standard deviation) and non-parametric (percentile) descriptors of the response distribution. In contrast, there seemed to be a normal distribution for the limb displacements at peak velocity and movement end.

To date, the majority of studies featuring the measure of spatial variability have assumed that differences in the standard deviation of limb locations at early (peak acceleration, peak velocity, peak deceleration) and late (movement end) stages of the movement represent influences of planning and control processes, respectively. For example, the decline in early kinematic landmarks across practice assumes the development of a more refined specification of motor efference (Hansen et al., 2005; Khan & Franks, 2003), while an exponential decline in variability toward the end of movement assumes the use of online

sensory feedback (Khan et al., 2003). While there has been no known study to precisely attribute the sources of this variability, we may have presently assumed that the within-participant variability was stochastic in nature, as per the matter of endpoint variability (Meyer et al., 1988) and the associated effective target width (Welford, 1968). Such trial-by-trial behaviour ought to generate a normal or Gaussian distribution of limb locations throughout the entire trajectory. However, the present data indicate that this assumption is premature at best as there were marked violations in the normal distributions at certain kinematic landmarks (peak acceleration, peak deceleration). Because the skewness was isolated to only some, and not all the landmarks, while a removal criteria (<100 ms and >1000 ms in reaction times, >800 ms in movement times) was set in advance of the analysis, it is highly unlikely that these findings were the result of some unnoticed artefact or failed movement/s (for examples of trial outliers, see Grierson & Elliott (2008) and Grierson, Lyons, & Elliott (2011)).

On further assessment of the trend of the response distributions; namely, the negative skew at peak deceleration, it is possible that we can derive even more detail about these particular aiming movements as opposed to attributing mere random error. That is, the current trend may represent potential contamination of within-participant variability based on a voluntary parameter such as an attempt of the performer to prematurely engage in deceleration. These rare instances may reflect an anomalous safe approach to the end target as an alternatively random or extended position to peak deceleration would be possibly associated with a normal and positively skewed distribution profile, respectively. This suggestion is consistent with the tenets of optimization as performers seek to avoid an overshoot because it may incur some cost in time and energy-expenditure (Lyons et al., 2006; Oliveira, Elliott, & Goodman, 2005). Along these lines, there is evidence to suggest that peak deceleration is reached at an earlier point in time and space when encountering an

unanticipated positive shift in limb-velocity compared to other limb-velocity perturbations (Grierson et al., 2011). In a similar vein, the potential of incurring an even greater cost of an overshoot when aiming downwards (requiring corrections against gravity) coincides with a shortened displacement at peak deceleration prior to 'homing-in' (Roberts, Burkitt, Elliott, & Lyons, 2016).

With this in mind, it is not unreasonable to suggest that the negative skew at peak deceleration pertains to the generation of early exploratory or alternative behaviours with a view to learning (Elliott et al., 2004; van Beers, 2009; Wolpert & Flanagan, 2010). Indeed, it has been previously shown that performers encounter profound changes in their target-directed movements and subsequent learning following feedback of previous trial events (Burkitt, Staite, Yeung, Elliott, & Lyons, 2015; Cheng, Luis, & Tremblay, 2008; Khan & Franks, 2003). Presumably, performers seek to explore how fast they can aim before accumulating an error (Rabbitt, 1981). In the event that the performer moves so fast that they almost miss or no longer subtend the target boundaries then they will limit their reach until variability is reduced (see Joseph, King, & Newell, 2013, for commentary on transitory learning phases).

On the contrary, it is important to realise that in the absence of any direct experimental manipulation designed to offset the variability measures from the current standard context, it cannot be categorically denied that such skewed profiles were the result of noise. Indeed, it is possible that the variance of positions for each kinematic landmark coincided with variations in time. That is, the acceleration landmarks may have reached varying moments in time (asymmetric), while the moment of peak velocity assumed a comparatively fixed period in time (symmetric). Nevertheless, this distinction between time and position ceases to be drawn within previous studies featuring spatial variability of kinematic landmarks, whose assumptions are of principle concern in the present study (see

Khan & Binsted, 2010, for examples of alternative moments of spatial variability). In order to positively attribute the sources of this variance, future investigations may seek to closely link single-trial events with ongoing (online; trial n) or subsequent (offline; trial $n+1$) target attempts in open- and closed-loop conditions. If the response distributions of kinematic landmarks are differentially sensitive to such manipulations then we can more strongly attribute these effects to systematic or intended sources of variance.

On a separate note, the reported differences between the ranges based on ±1SD and ±34.13[th] percentile, as well as the observed differences in within-participant means and medians (see Tables 1 and 2), continue to reflect the same form of variability profile (see Figures 2 and 4). That is, there was a systematic increase between peak acceleration and peak deceleration prior to a decline at the end of the movement. This form is deemed the characteristic feature of online control as changes between conditions should be primarily determined by relative rather than absolute metrics (Allsop et al., 2016; Khan et al., 2003). Thus, the presently conceived use and inference of spatial variability can successfully encompass variations across kinematic landmarks, although there may be some issues when separately comparing different levels of an independent factor (e.g., vision vs. no vision) at individual kinematics landmarks.

At this juncture, we begin to recognise that the use of spatial variability to-date may indiscriminately consist of random (involuntary) and systematic (voluntary) sources of variance that are associated with stochastic properties and trial-by-trial adaptation, respectively. Therefore, it is problematic to adopt this measure for the potential inference of effective limb position across certain points of the trajectory. At the same time, it may unreasonably inflate individual participant values and offer imprecise accounts of trial-by-trial behaviour. Thus, a more precise indication of pre-movement parameterization and intervening online control, designed to combat accumulating inherent and random sources of

variability, may be better-served by a non-parametric equivalent such as percentile ranges. Meanwhile, the potential inference of systematic variations within the trajectory (e.g., trial-by-trial adaptation) may be more appropriately represented by measures of skewness in the distribution of spatial locations.

In conclusion, while the current evidence does not refute the explanatory power of within-participant standard deviation as a measure of spatial variability, it does suggest that there is sufficient recourse to assess the distribution of limb locations; especially for landmarks of acceleration. Such procedures may be conducted with a view to selecting the appropriate descriptive statistics that closely reflect trial-by-trial behaviour. What's more, any such violation in normality (e.g., positive/negative trend) may be leveraged to infer particular or systematic motor behaviours. Future research may identify the factors that cause such variation within the distribution including, but not limited to, the influence of practice and task mastery. Based on the current trend, it is possible that the degree of skewness may become less with increasing practice so that any further variability that is incurred may be isolated to random stochastic properties.

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Tables

Table 1. Mean within-participant means (±SD) and medians (±34%) of the displacement at kinematic landmarks (mm) for cases aiming horizontal/forward

	PA	**PV**	**PD**	**END**
Mean (±SD)	10.53 (7.46-13.59)	98.59 (88.18-109.00)	212.25 (194.15-230.35)	239.18 (235.93-242.44)
Median (±34%)	9.75 (8.05-13.00)	98.64 (88.65-107.64)	214.92 (196.49-227.00)	238.88 (236.24-242.26)

Table 2. Mean within-participant means (±SD) and medians (±34%) of the displacement at kinematic landmarks (mm) for cases aiming vertical/upward

	PA	**PV**	**PD**	**END**
Mean (±SD)	7.08 (5.70-8.45)	59.75 (51.73-67.77)	138.17 (123.64-152.70)	156.33 (152.98-159.68)
Median (±34%)	7.07 (5.84-8.12)	58.98 (52.61-66.82)	140.83 (124.86-151.05)	156.45 (153.13-159.52)

Figure captions

Fig. 1 Combined within-participant frequency distributions of spatial locations at peak acceleration (PA), peak velocity (PV), peak deceleration (PD), and movement end (END) for the first set of movement data (horizontal/forward).

Fig. 2 Variability ranges defined by ± 1 standard deviation (SD) and $\pm 34.13^{th}$ percentile (%) across kinematic landmarks for the first set of movement data (horizontal/forward).

Fig. 3 Combined within-participant frequency distributions of spatial locations at peak acceleration (PA), peak velocity (PV), peak deceleration (PD), and movement end (END) for the second set of movement data (vertical/upward).

Fig. 4 Variability ranges defined by ± 1 standard deviation (SD) and $\pm 34.13^{th}$ percentile (%) across kinematic landmarks for the second set of movement data (vertical/upward).

Footnotes

1) Because the double-differentiated time-series displacement data used to obtain

   acceleration may have exaggerated any irregularities in the kinematics, it is possible that

   the indicators of skewness or non-normal distributions resulted from an artefact of data

   processing. Thus, the present findings were corroborated by conducting the same sets of

   analyses following the re-filtering of velocity data prior to a further three-point central

   differentiation. For z^3 scores, the main effect of kinematic landmark approached

   conventional levels of significance, $F(3, 30) = 2.67$, $p = .085$, *partial* $\eta^2 = .21$, while there

   was a significantly positive skew compared to 0 for peak acceleration, $t(10) = 2.55$, $p <$

   .05 (peak acceleration: $M = .32$, $SD = .42$; peak deceleration: $M = -.64$, $SD = 1.15$).

   Meanwhile, comparisons between standard deviation and percentile ranges revealed

   significant main effect of statistic, $F(1, 10) = 7.17$, $p < .05$, *partial* $\eta^2 = .42$, and

   kinematic landmark, $F(3, 30) = 32.76$, $p < .05$, *partial* $\eta^2 = .77$, although were superseded

   by a significant statistic x kinematic landmark interaction, $F(3, 30) = 4.65$, $p < .05$,

   partial $\eta^2 = .32$. Post hoc analysis confirmed a significantly larger range for standard

   deviation ($M = 31.59$, $SD = 9.24$) compared to percentile ($M = 26.29$, $SD = 12.65$) scores

   at peak deceleration ($p < .05$). Furthermore, as the transition between positive-to-

   negative acceleration coincides with the moment of peak velocity, the z^3 scores from the

   zero-line crossing of the double-differentiated acceleration were compared with the peak

   of the single-differentiated velocity, which revealed no significant difference, $T = 5$, $z =$

   .27, $p > .05$. Collectively, it appears these separate analyses refute suggestions of a

   processing artefact.

2) To further corroborate the additional analysis for horizontal/forward movements, the

   same data processing was undertaken for the vertical/upward movements to derive

   displacement in the acceleration trace following the filtering of velocity. Comparison of

the z^3 scores revealed a significant main effect of kinematic landmarks, $F(3, 45) = 9.93$,

$p < .05$, *partial η^2* = .40, which indicated a significantly more negative score at peak

deceleration ($M = -.89$, $SD = 72$) compared to the remaining landmarks (peak

acceleration: $M = .24$, $SD = .77$; peak velocity: $M = .32$, $SD = .68$; movement end: $M = -$

.15, $SD = .43$). These findings were corroborated by the single-sample t-test as there was

a significantly lower score compared to 0 for peak deceleration, $t(15) = 4.93$, $p < .05$.

Meanwhile, the analysis of standard deviation and percentile ranges showed significant

main effects of statistic, $F(1, 15) = 14.23$, $p < .05$, *partial η^2* = .49, and kinematic

landmark, $F(3, 45) = 61.61$, $p < .05$, *partial η^2* = .81, which were superseded by a statistic

x kinematic landmark interaction, $F(3, 45) = 4.29$, $p < .05$, *partial η^2* = .22. Post hoc

analyses confirmed a significantly larger standard deviation range ($M = 28.83$, $SD =$

7.78) than percentile range ($M = 24.49$, $SD = 10.12$) for peak deceleration ($p < .05$).

Finally, the comparison between the z^3 scores at peak velocity and corresponding

moment of the positive-to-negative zero-line crossing in acceleration revealed no

significant difference, $t(15) = .36$, $p > .05$.