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Combining unassisted and robot-guided practice benefits motor learning for a golf putting task

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Abstract

Robotic guidance has been employed with limited effectiveness in neurologically intact and patient populations. For example, our lab has effectively used robotic guidance to acutely improve movement smoothness of a discrete trajectory without influencing movement endpoint distributions (Manson et al., 2014). The purpose of the current study was to investigate the efficacy of combining robotic guidance and unassisted trials in the learning of a golf putting task.

Participants completed a pre-test, an acquisition phase, and an immediate and delayed (24-hour) post-test. During the pre-test, kinematic data from the putter was converted into highly accurate, consistent, and smooth trajectories delivered by a robot arm. During acquisition, 3 groups performed putts towards 3 different targets with robotic guidance on either 0%, 50% or 100% of acquisition trials. Only the 50% guidance group statistically reduced both the ball endpoint distance and variability between the pre-test and the immediate or 24-hr post-test.

The results of the 50% guidance group yielded seminal evidence that combining both unassisted and robotic guidance trials (i.e., mixed practice) could facilitate at least short-term motor learning for a golf putting task. Such work is relevant to incorporating robotic guidance for sport skills in and other practical areas (e.g., rehabilitation).

Keywords: robotic guidance, motor learning, principles of practice

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1. Introduction

When learning a new motor skill, there are many different approaches that an instructor may incorporate to help teach that motor skill. For example, a golf instructor may take hold of the club being used to physically guide an individual into the correct position to perform the novel skill (e.g., a putt). Physical guidance has been defined as, the act of "moving or being moved into a new position or location" (Hodges & Campagnaro, 2012, p. 179). More recently, physical guidance has been administered with the use of robotic devices. These robotic devices allow participants to be guided through an "ideal" trajectory to establish a reference of correctness (e.g., Adams, 1971) that is highly repeatable and delivers perfect performance on every trial. For example, robotic devices have been used to aid motor skill acquisition in non-clinical populations (Kümmel, Kramer, & Gruber, 2014; Manson et al., 2014; Marchal-Crespo & Reinkensmeyer, 2008a), as well as for rehabilitation purposes (Kwakkel, Kollen, & Krebs, 2008; Lugo-Villeda et al., 2009; Masiero et al., 2007). Although these studies have yielded beneficial results, it seems unclear as to how robotic guidance should be employed for motor skill acquisition to be most effective.

1.1. Physical guidance

Different methodologies have been used to assess robotic guidance's influence on motor skill acquisition in non-clinical populations. Specifically, at least two types of guidance have emerged in the literature. Studies have employed both error reduction (i.e., guiding the limb towards or with a correct reference: Kümmel et al., 2014; Manson et al., 2014; Marchal-Crespo, McHughen, Cramer, & Reinkensmeyer, 2010; Marchal-Crespo & Reinkensmeyer, 2008a) and error amplification guidance (i.e., increasing error, moving the limb further away from the correct reference: Marchal-Crespo, Schneider, Jaeger, & Riener, 2014; Williams, Tremblay, & Carnahan, 2016). Both the error reduction and error amplification approaches have been shown to be effective for enhancing performance and learning outcomes.

It has been shown that error reduction guidance can benefit movement timing, movement smoothness, and can alter the trajectory of the task being performed (Kümmel et al., 2014; Marchal-Crespo et al., 2010; Marchal-Crespo & Reinkensmeyer, 2008a; Marchal-Crespo & Reinkensmeyer, 2008b; Manson et al., 2014). Manson and colleagues (2014) demonstrated that robotic guidance was effective at inducing acute performance changes to the trajectory and smoothness of a simple aiming task. Importantly, a variable practice schedule (e.g., having participants aim to multiple targets) was employed. Variability of practice involves using different targets or movement parameters (see Schmidt, 1975) during the acquisition of motor skills and presumably helps identify and correct errors (e.g., Tremblay, Welsh, & Elliott, 2001). Although the above-mentioned study showed some promise, the evidence for the impact of robotic guidance on motor learning remains underwhelming outside of the context of simple aiming tasks.

In contrast, error amplification during robotic guidance has yielded results that seem to be relatively permanent (e.g., Marchal-Crespo et al., 2014; Williams et al., 2016). For example, Williams et al. (2016) showed that participants exposed to error amplification guidance when learning a tracing task had significantly better performance in both delayed retention and transfer tests compared to the error minimization group. The enhanced learning showed by the error augmentation group has been attributed to the increase in control processes used during acquisition. Although error amplification guidance resulted in enhanced learning, it is worth mentioning that participants still did not outperform acquisition without robotic guidance (i.e., no guidance). Because error amplification guidance does not yield better motor learning outcomes than no guidance, which can both be explained by the development of error detection and correction mechanisms (e.g., Williams et al., 2016), it remains unclear why error reduction guidance has an immediate impact on performance. Therefore, the current study aimed to test if error reduction guidance on trajectory accuracy combined with the motor learning benefits of unassisted practice (i.e., errorful performance) can further optimize the performance and learning of a novel golf putting task.

Although guidance has been shown to temporarily improve performance following skill acquisition (Marchal-Crespo et al., 2008a, 2008b, 2010, 2014), results have been inconsistent with regard to learning. As suggested above, one of the main reasons as to why learning may not occur is because of the lack of errors experienced when guidance is used. Schmidt (1975) suggested that if errors cannot take place, the strengthening of the motor response schema may not occur. Thus, when performing a specific task (e.g., a golf putt), the general sensory consequences (i.e., recognition schema) as well as the response specifications (e.g., large follow through: i.e., recall schema) are derived from past experiences (e.g., putting form various distances) instead of an exact “copy” (e.g., putting 8 feet: cf. Adams, 1971). Therefore, employing perfect physical guidance on every trial may not be beneficial to motor learning (e.g., Marchal-Crespo & Reinkensmeyer, 2008a), at least not as much as practice involving errors.

The feedback from guidance may initially cause rapid improvements in performance because it establishes a reference of correctness (e.g., recall and recognition schema: Schmidt, 1975). However, this improvement is sometimes short lived once guidance is removed (e.g., Marchal-Crespo & Reinkensmeyer, 2008a). Performance may decline after the removal of guidance because guidance is acting as a “crutch” for individuals (e.g., Salmoni, Schmidt, & Walter, 1984). Accordingly, the guidance hypothesis (Salmoni et al., 1984; Schmidt, Young, Swinnen, & Shapiro, 1989) suggests that external feedback (e.g., swing information in golf) is useful in that it helps improve performance. But, if this external feedback is given too often, it can be detrimental to performance during a retention test when robotic guidance and the associated feedback is removed (Salmoni et al., 1984; Schmidt, 1991; Schmidt et al., 1989). The reliance on external feedback would help explain why physical guidance given 100% of the time during acquisition is detrimental to motor learning (see Marchal-Crespo & Reinkensmeyer, 2008a). Overall, because error reduction guidance can help establish a strong reference of correctness and because unassisted/no guidance trials can help develop error detection and correction mechanisms, the motor schema theory and guidance hypothesis (Schmidt, 1975 and Schmidt et al., 1989, respectively) would predict that a combination of these methods would be more beneficial to motor learning than either of these practice methods.

The purpose of the current study was to investigate the influence that mixed practice (i.e., robotic guidance and unassisted trials) in combination with variable practice had on the learning of a golf putting task. To investigate the influence of mixed practice three groups that trained with different amounts of guidance were used (i.e., 0%, 50%, 100%) while incorporating variability of practice. It was hypothesized that combining acquisition trials that include both robotic guidance and no guidance (i.e., mixed practice), along with variability of practice principles (i.e., putting to multiple targets: Manson et al., 2014), would result in the largest improvements in performance and learning of a golf putting task. This improvement in performance and learning was expected because participants would alternate between perceiving an ideal reference of correctness during guidance trials and salient contrasts (i.e., errors) from the no guidance trials (see discussion). Also, based on the guidance hypothesis (Salmoni et al., 1984; Schmidt et al., 1989), a secondary hypothesis was that the group practicing only with robotic guidance would exhibit no improvements in performance following the removal of robotic guidance (i.e., 100% guidance group: e.g., Baker, 1968; Salmoni et al., 1984; Waters, 1930). \

2. Materials and methods

2.1. Participants

Thirty-three neurologically intact participants were recruited from the University of Toronto community (15 males and 18 females; M = 27.6 yrs, range = 17 - 43 yrs). All participants were self-declared right-hand dominant and had normal to corrected-to-normal vision. Each participant was randomly assigned to one of three different groups (i.e., no guidance group [NG], 50% guidance group [50-G], and 100% guidance group [100-G]) comprising of 11 participants per group (i.e., 5 males and 6 females). Each participant signed a consent form before taking part in the experiment. The study was approved by the Research Ethics Board at the University of Toronto. Participants received payment of $10/hr for their time.

2.2. Apparatus

Participants performed the novel golf putting task on a custom-built putting green (BirdieBall Putting Green, BirdieBall Inc., Wheat Ridge, CO, USA) measuring 488 cm long × 122 cm wide with three custom built circular Light-Emitting Diode (LED) targets and 1 LED home position (see Figure 1). These circular LED targets represented the outline of a golf hole measuring 10.8 cm in diameter and were constructed with 8 bright white circular LED's (i.e., 2 mm in diameter) per target. Three targets were inserted into the putting green at distances of: 192 cm (first target); 213 cm (second target); and 234 cm (third target) from the home position (i.e., measured from center to center) to ensure that the targets were of perceivably different amplitudes (Weber's Law see: Gescheider, 1997). The targets and home position for the ball were 52 cm from the left edge of the putting green and could not be seen if the LEDs were not illuminated. To ensure the ball was placed in the exact same place every single time, a small indent was made on the green so that the ball sat flush with the home position LED. Parallel to the putting green was a protective cage (L: 193 cm x W: 208 cm x H: 202 cm). This cage was used to protect participants from the Selective Compliant Assembly Robot Arm used for physical guidance trials (SCARA; Epson E2L853, Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN) which has the capability of moving in four degrees of freedom and is able to replicate a movement with a 0.02 mm spatial repeatability. An opening in the protective cage allowed the robot to be positioned directly in line with the home position on the floor. Because the robot was positioned outside of the cage an extension of the cage was built to insure participants could not come in direct contact with the robot (L: 48 cm x W: 208 cm). To perform each putt, participants used a Titleist Scotty Cameron Studio Select Newport 1.5 putter (Titleist Inc., Fairhaven, MA, USA) and a Nike SFT golf ball (Nike Inc., Beaverton, OR, USA). During robotic guidance trials a second Titleist Scotty Cameron Studio Select Newport 1.5 putter (Titleist Inc., Fairhaven, MA, USA) was connected to the robot with a custom-built connection with the golf putter head (see Figure 1).

For the acquisition phase, three trajectories unique to each participant (i.e., made for each golf hole) were programmed into the robot. These trajectories were based on each participants Pre-Test three-dimensional putts which were recorded and sampled at 250 Hz using an infrared emitting diode (IRED) secured to the inside front edge of the putter. The IRED was tracked by an Optotrak Certus system (Northern Digital Inc., Waterloo, ON, Canada). IRED position data of the putter trajectory were filtered using a second order, dual-pass, Butterworth, 15Hz low pass cut-off filter. The start and the end of both the backstroke and forward stroke of the golf putt were identified when the putting head IRED velocity rose above and fell below 30 mm/s for 3 consecutive samples. These trajectories were first averaged over fifteen trials and then filtered using a polynomial fit function with a custom MATLAB (i.e., polyfit function; The MathWorks Inc., Natick, MA, USA) script yielding a smooth trajectory for each participant. Also, to ensure perfect contact with the ball, the participants' putting strokes were constrained to a constant value along the secondary movement axis (i.e., no motion of the robot in the X-axis: see Figure 1). Once the first trajectory was made for target 2 (i.e., Pre-Test target) the other two trajectories were scaled in the primary movement axis (i.e., putt amplitude: Y-axis) by ± 10 %, to shorten or lengthen the putts for the closest or farthest target accordingly. Once the other trajectories were calculated, the peak velocity and peak acceleration values were scaled as well to ensure participants putts with the robot were successful (i.e., stopped on or just beyond the hole consistently). The robot arm was controlled by using a custom SPEL + program (Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN) interfacing with MATLAB (The MathWorks Inc., Natick, MA, USA).

*****Figure 1 near here*****

2.3. Task and Procedure

The task required participants to perform a three-dimensional golf putt to three different LED targets. This golf putting task was considered extremely difficult and novel as participants were instructed to try and stop the ball on the center of the target. Unlike a typical golf putt where the ball falls into the hole, this task required more precise putt distance control so that the ball did not go through or past the hole accordingly. Before each trial, the home position and a single target were presented. Prior to approaching the golf ball, participants were instructed on how to grip the putter with an overhand putting grip as well as to stand with their feet shoulder width apart with the ball in the center of their stance. Participants were then asked to place the putter behind the golf ball as closely as possible as well as align the middle of the putter head with the middle of the golf ball. Once aligned, participants were then asked to focus on the target prior to the beginning of each trial.

To signal the beginning of each trial, a double-beep was emitted by a piezo-electric buzzer (Mallory Sonalert Products Inc.: Model SC628, tone frequency of 2900 Hz) sounded. Once this had occurred participants were then asked to shift their focus onto the golf ball and prepare to execute the golf putt to the specified target displayed. Following a 2 second delay, a third beep sounded, which instructed participants to begin their putt. Participants were given 3 seconds to complete their putt (i.e., backstroke and follow through) before a fourth beep sounded signaling the end of the trial.

The experiment consisted of four experimental phases: Pre-Test, Acquisition, Immediate-Retention (Imm-Ret: i.e., following acquisition), and Delayed-Retention (Del-Ret: i.e., 24-hours following acquisition) testing phases. Participants performed 5 familiarization trials to the 2nd target to become used to the task prior to completing a 15 trial Pre-Test to the same target. During both the familiarization and Pre-Test phases, no visual feedback of the target was given (i.e., one second following the trial auditory pre-cue, the target disappeared). This was done to reduce the amount of short-term learning that may take place during the Pre-Test.

Following the familiarization and Pre-Test, participants were put into one of three different acquisition groups. The first group was not guided by the robotic arm during the acquisition trials (i.e., no guidance group [NG]), the second group was guided by the robotic arm for half of the acquisition trials (i.e., 50% guidance group [50-G]), while the third group was guided by the robotic arm for all of the acquisition trials (i.e., 100% guidance group [100-G]). If participants were put into a robotic guidance group, they performed an additional 5 robotic guidance familiarization trials with a trajectory that was not their own but was consistent across all participants. When participants were guided by the robot they were instructed to 'focus on the position of the backswing and to try their best to reproduce the velocity or speed that the robot produced.' Participants were also asked to actively follow the robot and were told that if they did not then this would reduce the accuracy of the golf putt being performed by slowing down the robot or speeding it up accordingly.

Throughout the acquisition phase, participants followed a variable practice protocol and putted to all three of the targets that were randomly presented every three trials for 120 trials (i.e., 40 trials for each target). As raised in the introduction, variability of practice was employed because it can facilitate motor learning (Shea & Kohl, 1990; 1991) and influence sensory feedback utilization (Tremblay et al., 2001). All trials with robotic guidance were from the participant's own trajectories in the pre-test. Throughout the acquisition trials, the target remained visible, allowing participants visual feedback of where the ball ended in relation to the target. For the 50-G group participants alternated between 12 robotic guidance trials and 12 no guidance trials until acquisition was completed. Participants always started acquisition with robotic guidance and ended with no guidance.

Following the acquisition phase, participants performed the Imm-Ret test, which was the exact same as the Pre-Test. Twenty-four hours following the acquisition phase participants returned and completed the Del-Ret testing phase. Again, participants performed 20 trials, consisting of 5 familiarization trials and 15 test trials, all towards the 2^{nd} target.

2.4. Performance Measures

Performance data (i.e., ball endpoint location) was recorded with the use of a grid system. The custom grid consisted of squares measuring 30 cm × 30 cm. The grid began from the home position where the ball was placed for each putt. From there, each line away from that position (i.e., measuring 30 cm apart) in the primary direction (positive on the Y-axis: see Figure 1). Similarly, the secondary movement axis relative to the grid (i.e., X-axis), started from the left side of the putting green. The large grid ball endpoint location was recorded in MATLAB and stored for later analyses. To determine where the ball landed specifically within the identified square, photos were taken of the ball location within each square with a custom-built camera holder. Each picture was then used with a custom MATLAB script where the ball and square were selected to calculate the exact position in which the ball was located within the specified square, which yielded the exact location of the center of the ball on the green, to the nearest millimeter. This information was then used to calculate constant error in the primary movement axis (i.e., CEY: overshoot [+] and undershoot [-]), constant error in the secondary movement axis (i.e., CEX: left [-] and right [+]), as well as variable error in both movement axes (i.e., VEY and VEX) accordingly.

2.5. Acquisition Phase Data

In order to demonstrate the influence of robotic guidance trials during acquisition, variable error in the primary and secondary movement axes (VEY and VEX) as well as constant error in both movement axes (CEX and CEY) were recorded and displayed (see Table 2 and Figure 2 for visual depiction of VEY and CEY during all experimental phases). To assess the influence of robotic guidance during acquisition trials, the acquisition data was separated based on the blocks of 12 trials in which it was implemented (e.g., for the 50-G group alternated between 12 guidance and 12 no guidance trials). As a result, comparisons could be made within each individual group. Also, although the acquisition trials were performed to three different targets, there were only four trials per target in each block. As a result of participants only performing four trials to each target per block, performance measures were collapsed across targets for each block of twelve trials in the acquisition phase. To investigate if participants performance improved during acquisition, unassisted trials (i.e., without guidance) trials were compared using separate repeated measures ANOVAs (i.e., NG × 10 Blocks, 50-G × 5 Blocks). To assess the performance and task consistency of the robotic guidance trials (i.e., guided trials), participants guided trials were compared using separate repeated measures ANOVAs also (i.e., 100-G × 10 Blocks, 50-G × 5 Blocks). If a significant effect was identified ($p < .05$), multiple dependent sample T-tests were conducted comparing the 1st Block to all subsequent Blocks, with a Bonferroni correction applied accordingly (i.e., for the NG and 100-G groups α corrected = .05/9 = .006, and for the 50-G α corrected = .05/4 = .01). No between group comparisons were made due to the expected unequal variance between the robot-guided trials (i.e., for the 100-G and 50-G groups) and for the unassisted trials (i.e., for the 0-G and 50-G groups).

*****Table 1 near here*****

2.6. Testing Phases Data and Analyses

To assess if an improvement in performance and if learning had likely taken place following acquisition, our performance measures consisted of variable error in the primary and secondary movement axes (VEY and VEX) as well as constant error in the primary and secondary movement axes (CEY and CEX) respectively.

All variables were analyzed using separate 3 Phase (i.e., Pre-Test, Imm-Ret, Del-Ret) × 3 Group (i.e., NG, 50-G, 100-G) mixed model ANOVAs, with Phase as a within-subjects factor and Group as a between-subjects factor. Based on the hypothesis that the group that experiencing mixed practice (i.e., 50-G group) would significantly improve their task performance and learning, pre-planned contrasts between the Pre-Test and both the Imm-Ret, and Del-Ret tests within each group were conducted using dependent sample T-tests if a significant main effect was identified ($p < .05$). A Bonferroni correction (i.e., α corrected = .05/6 = .008) was also applied because of the 6 T-tests conducted for each variable). Partial eta squared effect sizes were reported for these analyses as well as Cohen's d_z to measure the strength of the influence of the acquisition phase for the difference between the Pre-Test to the Imm-Ret and Del-Ret testing phases (Lakens, 2013). Means and between subject SDs are reported in Table 2.

Table 2 Near Here

3. Results

3.4. Acquisition Phase

For brevity, only the significant differences were reported for the dependent sample T-tests as a result of the number of comparisons that needed to be made. Analysis of CEY during acquisition of the NG group yielded a significant effect of Block, $F(9, 90) = 2.176$, $p = .031$, $\eta_p^2 = .179$, but did not yield any significant differences when comparing all blocks to the first block of acquisition. The 100-G group did not yield a significant effect of Block, $F(9, 90) = .806$, $p = .612$, as well as the 50-G group for both the Unassisted trials, $F(4, 40) = 1.836$, $p = .141$, $\eta_p^2 = .155$, and Guided trials, $F(4, 40) = 1.116$, $p = .363$.

Analysis of CEX during acquisition failed to yield any significant effect of Block for the NG group, $F(9, 90) = .376$, $p = .944$, $\eta_p^2 = .036$, 100-G group, $F(9, 90) = 1.168$, $p = .325$, $\eta_p^2 = .105$, or the 50-G group for both the Unassisted trials, $F(4, 40) = 1.669$, $p = .176$, $\eta_p^2 = .143$, and Guided trials, $F(4, 40) = .747$, $p = .566$, $\eta_p^2 = .070$.

Analysis of VEY during acquisition failed to yield any significant effect of Block for both the NG group, $F(9, 90) = 1.901$, $p = .062$, $\eta_p^2 = .160$, and the 100-G group, $F(9, 90) = .719$, $p = .690$, $\eta_p^2 = .067$. However, analysis of VEY yielded significant differences in the 50-G group for both the Unassisted trials, $F(4, 40) = 3.621$, $p = .013$, $\eta_p^2 = .266$, and Guided trials, $F(4, 40) = 2.867$, $p = .035$, $\eta_p^2 = .223$. Although this was the case, no significant differences were identified when comparing all blocks to the first block of acquisition.

3.5. Testing Phases

Analysis of CEY yielded a significant main effect of Phase, $F(2, 60) = 10.772$, $p < .001$, $\eta_p^2 = .264$. The Phase × Group interaction was not significant, $F(4, 60) = .407$, $p = .803$, $\eta_p^2 = .026$. A- priori pre-planned comparisons clarified the main effect of Phase for the 50-G group, $t(10) = 3.520$, $p = .006$ (dz = 1.06). It was identified that participants in the 50-G group significantly improved their performance in the Del-Ret testing phase (M = .03 cm, stopping the ball on the target) when compared to the Pre-Test (M = 20.8 cm, putting the ball past the target: see Figure 2). No significant differences were identified when comparing the Pre-Test to the Imm-Ret testing phase for the NG group, $t(10) = 2.046$, $p = .068$, 50-G group, $t(10) = 1.816$, $p = .099$, or the 100-G group, $t(10) = 2.280$, $p = .046$. No significant differences were also identified when comparing the Pre-Test to the Del-Ret testing phase for both the NG group, $t(10) = 1.761$, $p = .109$, and the 100G group, $t(10) = 2.062$, $p = .066$.

The analysis of CEX yielded no significant main effect of Phase, $F(2, 60) = 1.582$, $p = .214$, $\eta_p^2 = .050$, Group, $F(2, 30) = .770$, $p = .472$, $\eta_p^2 = .049$, or interaction between Phase × Group, $F(4, 60) = .628$, $p = .645$, $\eta_p^2 = .040$.

Analysis of VEY yielded a significant main effect of Phase, $F(2, 60) = 10.019$, $p < .001$, $\eta_p^2 = .250$. The Phase × Group interaction was not significant, $F(4, 60) = 1.260$, $p = .294$, $\eta p2 = .077$. A- priori pre-planned comparisons clarified the main effect of Phase for the 50-G group, $t(10) = 4.099$, $p < .003$ (dz = 1.24) exhibiting a reduction in VEY from the Pre-Test to the Imm-Ret testing phase (see Figure 2). No significant differences were identified when comparing the Pre-Test to the Imm-Ret testing phase for both the NG group, $t(10) = 2.967$, $p = .014$, and the 100-G group, $t(10) = .590$, $p = .568$. No significant differences were also identified when comparing the Pre-Test to the Del-Ret testing phase for the NG group, $t(10) = 2.269$, $p = .047$, 50-G group, $t(10) = 2.997$, $p = .013$, and the 100G group, $t(10) = .377$, $p = .714$.

The analysis of VEX yielded no significant main effect of Phase, $F(2, 60) = 1.756$, $p = .181$, $\eta_p^2 = .055$, Group, $F(2, 30) = 1.486$, $p = .243$, $\eta_p^2 = .090$, or interaction between Phase × Group, $F(4, 60) = 1.920$, $p = .119$, $\eta_p^2 = .113$. [1]

4. Discussion

The current study contrasted the effects of trials with robotic guidance and no guidance on the learning of a golf putting task. As such, the core aims of the proposed experiment were to investigate and understand the impact of combining physical guidance and unassisted practice on the execution of a complex multiple-segment movement (i.e., a novel golf putting task). This was done while employing principles of practice known to optimize motor learning (e.g., variability of practice: Shea & Kohl, 1990; 1991) and perhaps contributed to avoiding the negative impacts of some robotic guidance protocols on the learners' motivation (e.g., Duarte & Reinkensmeyer, 2015). As hypothesized, only the group who underwent mixed practice improved both on constant error (CEY) and endpoint variability (VEY) performance for the golf putting task (i.e., in the immediate and delayed retention test, respectively). These results indicated that combining guidance and no guidance trials can improve task performance and consistency of a golf putting task. Also, as per the secondary hypothesis, practicing only with robotic guidance did not yield any improvements in performance. Finally, it is important to note that the NG group also did not exhibit any significant performance improvements for any of the performance measures during this single-day acquisition phase.

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[1] Although there were no significant interactions for all variables, this was a likely statistical outcome as a direct result of all groups improving due to experiencing variability of practice. However, main effects of phase were present, and it was hypothesized that incorporating unassisted trials would lead to an improvement in performance. It was also hypothesized that experiencing guidance for all trials (i.e., 100-G group) would result in a lack of improvement. As a result of the proposed hypotheses, there was a clear rationale for making within-group comparisons to further understand which groups may have improved as a direct result of the type of acquisition trials experienced.

Although all groups did improve constant error in the primary movement axis, the only group to statistically improve from the Pre-Test to the Del-Ret test was the 50-G group. Specifically, the 50-G group in the Del-Ret testing phase on average stopped the ball with a constant error of 0.03 cm (i.e., stopping the ball on the hole). The improvement in the 50-G group was likely the result of improved detection and correction of their own errors. This improvement in error detection/error correction mechanisms may have been improved using the ideal reference of correctness provided consistently by the robotic guidance. This ideal reference of correctness was provided consistently by the robotic guidance during the acquisition trials (i.e., less variability compared to unassisted trials). The robotic guidance trials replicated expert performance as expert performance is defined as consistent superior performance over an extended period (Starkes, 1993).

Such benefit of mixed practice (i.e., experiencing a perfect reference of correctness [expert performance] as well as one's own errors) has also been reported for observational learning, which arguably involves similar error detection and correction mechanisms comparable to physical practice (e.g, Blandin & Proteau, 2000). Andrieux and Proteau (2013; 2014) tested how an expert model and a novice model (i.e., mixed observation) can help an observer learn a sequential motor skill better than when solely observing an expert or a novice model. The authors identified that, when learning a novel barrier knockdown task, experiencing both an expert and novice model with physical practice, resulted in both improved short-term and long-term retention performance. The authors concluded, that allowing participants to experience both expert and novice performance as well as physically practicing the movement, errors likely became more salient or detectable. Due to errors being more salient, participants were able to better correct for their errors and improved their performance. Similarly, in the current investigation, experiencing both an expert performance (i.e., robotic guidance trials with greater consistency) and novice performance (i.e., no guidance trials with greater variability) potentially enhanced participants ability to detect when errors occurred and how to correct them accordingly. Comparing their performance and the ideal trajectory, likely allowed participants to evaluate their own errors and make adjustments to their trajectory accordingly. These different contributions of the reference of correctness and error identification mechanisms can explain the significant improvements in constant error and variability within the 50-G group (see below).

To investigate if the consistency of the task being performed improved following acquisition, variability of the ball endpoint position was evaluated (i.e., VEY & VEX) and indicated that the 50-G group exhibited reduced putting variability from the Pre-Test to the Imm-Ret testing phase in the primary movement axis. The improvement of ball endpoint variability in the 50-G group may be the result of experiencing both errors (i.e., no guidance trials) as well as the ideal performance (i.e., robotic guidance trials) during acquisition (i.e., mixed practice: see also Andrieux & Proteau, 2013; 2014).

For the individuals in the 50-G group, the guidance trials likely allowed to create a reference of correctness (e.g., recall and recognition schema: Schmidt, 1975) while the subsequent no guidance trials also allowed to detect errors. One could have predicted that the fixed guidance provided by the robot should have yielded “only temporary boosts to performance” (Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2019; pp. 338) and suggest that other forms of guidance are preferable (partial guidance: e.g., Marchal Crespo & Reinkensmeyer, 2008b, or error-augmenting guidance: e.g., Williams, Tremblay, & Carnahan, 2016). However, the results of the current study can be explained by a reference of correctness obtained from the guidance trials, that was in turn used during the subsequent no guidance trials to improve error detection and correction. One method to determine the ability to detect errors is to remove visual feedback at ball impact and ask the participant to estimate where the ball stopped on the green. We have recently conducted such an experiment, directly testing the influence of mixed robotic guidance on error detection (see Bested, de Grosbois, Crainic, & Tremblay, 2019). As expected, using the same single-day acquisition protocol, participants improved their ability to estimate the ball endpoint only if they were in a 50-G group (i.e., not in a NG group). As a result, interspersing no guidance trials between guidance trials represents a viable method to leveraging the strong reference of correctness provided by "fixed" guidance while avoiding its adverse effects.

In contrast, the 100-G group did not get to experience their own performance (i.e., errors) during acquisition. Although the 100-G group experienced what the "ideal" or "perfect" putt should feel like (i.e., proprioceptive information), as Schmidt (1975) illustrates, further development of the motor response schema would not occur without one's own experience (i.e., error). During acquisition, the 100-G group exhibited low variability in task performance (see Figure 3). This was expected as participants performed all trials during acquisition with robotic guidance. Because of this lack of experience (i.e., error) and lack of variability, participants would have had to rely on the close and farther target distances experienced during acquisition to correct their movements accordingly. This lack of error labelling during acquisition may have resulted in participants not being able to potentially develop error detection/ correction mechanisms important for learning to take place.

It should also be noted that performance of the 100-G group did not significantly improve following the acquisition phase as the guidance hypothesis would predict (Schmidt et al., 1989). Although participants did not significantly improve their performance in CEY there was a nonsignificant improvement. It is possible that participants benefited from the variability of practice principles (see Shea & Kohl, 1990; 1991) involved by employing the random presentation of multiple targets during acquisition (see also Manson et al., 2014). This may also be the reasoning as to why there was no significant improvement in any of the groups in CEY in the Imm-Ret testing phase. It seems that, as a result of experiencing variability of practice, all groups improved to a certain degree (see Figure 2). The influence of variability of practice on other sensorimotor learning processes has also been shown for the use of visual information as a function of practice. Indeed, Tremblay and colleagues (2001) showed that performance decrements arising from the withdrawal of visual feedback between an acquisition and a transfer test (re.: specificity of practice hypothesis: see Proteau, 1992; Tremblay, 2010) can be prevented if a variable practice protocol is employed. In Tremblay et al. (2001), participants practiced an aiming task with or without visual feedback, and that is with 1 or 5 targets. After the acquisition phase, all participants aimed to a single target without visual feedback. Critically, the performance decrements associated with the loss of vision were not as large for the groups practicing with 5 targets (i.e., variable practice) than the groups practicing with 1 target. The authors suggested that variable practice may have led to the integration of other sources of information for task performance. In the present study, it is possible that variable practice combined with robotic guidance may have promoted the use of a proprioceptive reference for target array and thus help identify errors when vision is removed. Because of the task difficulty in the current study, experiencing the reference of correctness provided by the robotic guidance and the variability of practice may have allowed participants to not rely on guidance following its removal (i.e., Imm-Ret and Del-Ret testing phases).

Although the results did reveal significant reductions in the 50-G group across the testing phases, in VEY and CEY, these significant improvements were not consistent. As such, it should be noted that these results were attained over a single practice session. The differences identified in the two different delayed testing sessions only for the 50-G group may be the result of the difficulty of the task being performed and that the learning of this complex task may take longer to master (i.e., both for precision and accuracy). Indeed, we would expect that practice without physical guidance (i.e., NG group) would eventually yield significant improvements in performance and learning.

In conclusion, it appears that practice regimes that include both guidance and no guidance trials (i.e., mixed practice) can benefit the short-term learning of a golf putting task. Specifically, only the 50-G group exhibited improvements both in the average ball endpoint location and consistency, while the other two groups failed to significantly improve in both of these domains. From this investigation, we have identified that for complex tasks such as a novel golf putt, robotic guidance allows participants to experience the "ideal" or "perfect" performance, which does not occur as frequently (as demonstrated by the consistency of the robotic guidance trials: see Figure 2), when compared to performing the task with no guidance. It may be that allowing one to experience the ideal trajectory, more consistently, and with their own performance (i.e., the inclusion of errors), results in enhanced error detection/ error correction mechanisms therefore improving motor performance and learning. Critically, further investigations of the influence of robotic guidance on error detection/ error correction mechanisms are needed.

Disclosure statement

The authors report no conflict of interest.

References

Adams, J. A. (1971). A Closed-Loop Theory of Motor Learning. *Journal of Motor Behavior, 3*(2), 111–150.

Andrieux, M., & Proteau, L. (2013). Observation learning of a motor task: who and when? *Experimental Brain Research, 229*(1), 125–137.

Andrieux, M., & Proteau, L. (2014). Mixed observation favors motor learning through better estimation of the model's performance. *Experimental Brain Research, 232*(10), 3121–3132.

Baker, C. H. (1968). An evaluation of guidance in learning a motor skill. *Canadian Journal of Psychology/Revue canadienne de psychologie, 22*(3), 217.

Blandin, Y., & Proteau, L. (2000). On the cognitive basis of observational learning: Development of mechanisms for the detection and correction of errors. *The Quarterly Journal of Experimental Psychology, 53A(3)*, 946-867.

Bested, S. R., de Grosbois, J., Crainic, V. A., & Tremblay, L. (2019). The influence of robotic guidance on error detection and correction mechanisms. *Human movement science, 66,* 124-132.

Duarte, J. E., & Reinkensmeyer, D. J. (2015). Effects of robotically modulating kinematic variability on motor skill learning and motivation. *Journal of Neurophysiology, 113*(7), 2682–2691. doi:10.1152/jn.00163.2014

Gescheider, G. (1997). Psychophysics: the fundamentals Lawrence Erlbaum. London: Routledge.

Hodges, N. J., & Campagnaro, P. (2012). Chapter 9: Physical guidance research. *Skill Acquisition in Sport: Research, Theory and Practice,* 150. New York: Routledge.

Kümmel, J., Kramer, A., & Gruber, M. (2014). Robotic guidance induces long-lasting changes in the movement pattern of a novel sport-specific motor task. *Human Movement Science, 38,* 23-33.

Kwakkel, G., Kollen, B. J., & Krebs, H. I. (2008). Effects of robot-assisted therapy on upper-limb recovery after stroke: A systematic review. *Neurorehabilitation and Neural Repair, 22*(2), 111-121.

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Frontiers in psychology, 4,* 863.

Lugo-Villeda, L. I., Frisoli, A., Sandoval-Gonzalez, O., Padilla, M. A., Parra-Vega, V., Avizzano, C. A., … Bergamasco, M. (2009). Haptic guidance of Light-Exoskeleton for arm-rehabilitation tasks. RO-MAN 2009 - *The 18th IEEE International Symposium on Robot and Human Interactive Communication.*

Manson, G. A., Alekhina, M., Srubiski, S. L., Williams, C. K., Bhattacharjee, A., & Tremblay, L. (2014). Effects of robotic guidance on sensorimotor control: Planning vs. online control? *NeuroRehabilitation, 35*(4), 689-700.

Marchal-Crespo, L., Furumasu, J., & Reinkensmeyer, D. J. (2010). A robotic wheelchair trainer: design overview and a feasibility study. *Journal of NeuroEngineering and Rehabilitation, 7*(1), 40.

Marchal-Crespo, L., Schneider, J., Jaeger, L., & Riener, R. (2014). Learning a locomotor task: with or without errors? *Journal of NeuroEngineering and Rehabilitation, 11*(1), 25.

Marchal-Crespo, L., McHughen, S., Cramer, S. C., & Reinkensmeyer, D. J. (2010). The effect of haptic guidance, aging, and initial skill level on motor learning of a steering task. *Experimental Brain Research, 201*(2), 209-220.

Marchal-Crespo, L. M., & Reinkensmeyer, D. J. (2008a). Haptic guidance can enhance motor learning of a steering task. *Journal of Motor Behavior, 40*(6), 545-557.

Marchal-Crespo, L., & Reinkensmeyer, D. J. (2008b) Effect of robotic guidance on motor learning of a timing task. *In: Biomedical Robotics and Biomechatronics,* 2008. BioRob 2008. 2nd IEEE RAS & EMBS International Conference on 19–22 Oct 2008, pp 199–204.

Masiero, S., Celia, A., Rosati, G., & Armani, M. (2007). Robotic-assisted rehabilitation of the upper limb after acute stroke. *Archives of Physical Medicine and Rehabilitation, 88*(2), 142-149.

Proteau, L. (1992). On the specificity of learning and the role of visual information for movement control. *In Advances in Psychology (Vol. 85*, pp. 67-103). L., Proteau & D. Elliot. Amsterdam, North-Holland: Elsevier.

Salmoni, A. W., Schmidt, R. A., & Walter, C. B. (1984). Knowledge of results and motor learning: a review and critical reappraisal. *Psychological Bulletin, 95*(3), 355-386.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review, 82*(4), 225-260.

Schmidt, R. A. (1991). Frequent augmented feedback can degrade learning: Evidence and interpretations. *In J. Requin & G. E. Stelmach (Eds.), Tutorials in Motor Neuroscience* (pp. 59–75). Dordrecht: Kluwer Academic Publishers.

Schmidt, R. A., Lee, T. D., Winstein, C. J., Wulf, G., & Zelaznik, H. N. (2019). *Motor Control and Learning: A Behavioral Emphasis.* Champaign, IL: Human Kinetics.

Schmidt, R. A., Young, D. E., Swinnen, S., & Shapiro, D. C. (1989). Summary knowledge of results for skill acquisition: support for the guidance hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15*(2), 352.

Shea, C. H., & Kohl, R. M. (1990). Specificity and variability of practice. *Research Quarterly for Exercise and Sport, 61*(2), 169-177.

Shea, C. H., & Kohl, R. M. (1991). Composition of practice: Influence on the retention of motor skills. *Research Quarterly for Exercise and Sport, 62*(2), 187-195.

Starkes, J. L. (1993). Motor experts: Opening thoughts. *In Advances in psychology (Vol. 102*, pp. 3-16). J. L., Starkes & F. Allard. Amsterdam, North-Holland: Elsevier.

Tremblay, L. (2010). Visual information in the acquisition of goal-directed action. Vision and Goal-Directed Movement: *Neurobehavioral Perspectives,* 281-291. Leeds, UK: Human Kinetics.

Tremblay, L., Welsh, T. N., & Elliott, D. (2001). Specificity versus variability: effects of practice conditions on the use of afferent information for manual aiming. *Motor Control, 5*(4), 347-360.

Waters, R. H. (1930). The influence of large amounts of manual guidance upon human maze learning. *The Journal of General Psychology, 4*(1-4), 213-228.

Williams, C. K., Tremblay, L., & Carnahan, H. (2016). It pays to go off-track: practicing with error-augmenting haptic feedback facilitates learning of a curve-tracing task. *Frontiers in Psychology, 7,* 2016.

Figure 1. 2D rendering of the experimental set-up. Kinematic data of the putter was recorded by using an Optotrak 3D motion capture system, which was mounted on a custom-built stand on the right side of the putting green. Y-axis arrow depicts the primary movement axis (i.e., backstroke and follow through) and X-axis arrow depicts the secondary movement axis.

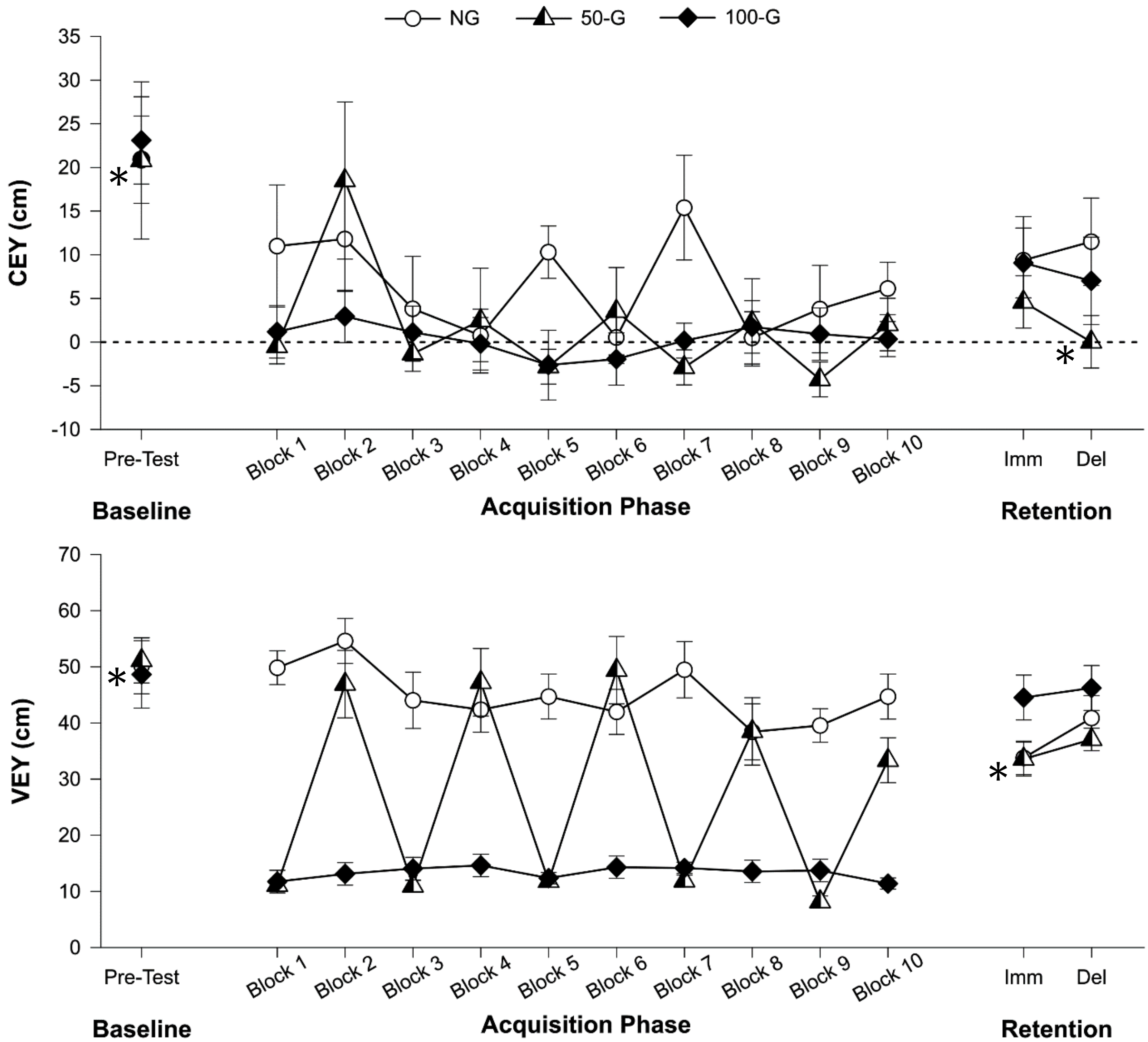

Figure 2. Top: Constant error in the primary movement axis (CEY: dotted line represents middle of target), Bottom: Variable error in the primary movement axis (VEY), for each group (i.e., NG, 50-G, and 100-G) across each experimental phase (i.e., Baseline: Pre-Test, Acquisition, and Retention: Imm-Ret and Del-Ret). Note: Acquisition phase was broken down into 12 blocks (i.e., including all three targets). This also allowed to visually depict the 50-G group alternating between guidance and no guidance trials. Error bars represent the standard error of the mean and (*) represents significant differences from the Pre-Test to the Imm-Ret and Del-Ret test for the 50-G group.

Table 1

Means and between-subject SDs for performance measures for all acquisition trial blocks (Blocks 1-10) for all groups: No Guidance (NG), 50% Guidance (50-G), and 100% Guidance (100-G).

	Group	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8	Block 9	Block 10
CEY (cm)	NG	11.0(25)	11.8(20)	3.8(19)	0.8(10)	10.3(10)	0.5(11)	15.4(21)	0.5(11)	3.8(15)	6.1(10)
	50-G	-0.5(8)	18.5(30)	-1.3(8)	2.5(19)	-2.8(7)	3.5(16)	-2.9(6)	2.3(15)	-4.3(8)	2.0(11)
	100-G	1.2(11)	2.9(11)	1.1(12)	-0.2(9)	-2.6(12)	-1.9(11)	0.2(8)	1.7(11)	0.9(9)	0.4(7)
CEX (cm)	NG	2.1(2)	2.0(3)	1.6(3)	1.7(3)	2.7(3)	2.3(3)	1.7(4)	2.4(2)	1.8(4)	1.4(3)
	50-G	3.9(1)	2.7(4)	3.7(1)	1.3(3)	3.5(2)	1.1(4)	3.6(1)	3.0(2)	3.2(1)	0.6(4)
	100-G	3.5(1)	4.0(1)	3.3(2)	2.8(2)	2.7(3)	3.1(2)	2.9(1)	3.8(1)	3.3(1)	3.7(1)
VEY (cm)	NG	49.8(10)	54.6(12)	44.0(18)	42.4(14)	44.7(12)	42.0(13)	49.5(16)	38.4(17)	39.5(9)	44.7(13)
	50-G	11.1(3)	46.9(21)	11.0(4)	47.2(18)	11.8(3)	49.4(20)	11.9(5)	38.5(20)	8.2(3)	33.4(12)
	100-G	11.7(6)	13.1(5)	14.1(7)	14.6(7)	12.4(4)	14.3(7)	14.2(4)	13.6(7)	13.7(8)	11.4(4)
VEX (cm)	NG	5.8(3)	6.5(3)	5.3(3)	5.6(2)	5.2(2)	4.4(2)	6.0(3)	4.9(3)	5.7(2)	6.3(3)
	50-G	2.3(1)	7.1(5)	2.4(1)	6.5(3)	3.0(2)	6.3(3)	2.3(0.5)	4.3(2)	2.6(2)	5.4(2)
	100-G	2.5(1)	2.5(1)	2.9(1)	2.9(1)	3.7(2)	3.6(2)	3.2(2)	2.2(1)	3.2(2)	2.7(1)

Note. CEY = constant error in the primary movement axis, CEX = constant error in the secondary movement axis, VEY = variable error in the primary movement axis, VEX = variable error in the secondary movement axis.

Table 2

Means and between-subject SDs for the performance measures for all groups: No Guidance (NG), 50% Guidance (50-G), and 100% Guidance (100-G) as a function of experimental phase (Pre-Test, Immediate-Retention [Imm-Ret], and Delayed-Retention [Del-Ret]).

	NG			50-G			100-G		
	Pre-Test	Imm-Ret	Del-Ret	Pre-Test	Imm-Ret	Del-Ret	Pre-Test	Imm-Ret	Del-Ret
CEY (cm)	20.9(16)	9.4(17)	11.5(15)	20.8(29)	4.6(11)	0.03(13)	23.1(16)	9.1(14)	7.0(18)
CEX (cm)	2.5(3)	2.9(2)	2.7(2)	2.6(5)	1.2(2)	2.9(1)	2.0(4)	0.5(4)	2.3(3)
VEY (cm)	50.2(17)	33.8(8)	40.9(13)	51.1(12)	33.0(10)	37.6(8)	48.6(21)	44.5(14)	46.2(14)
VEX (cm)	5.9(3)	6.1(5)	6.7(2)	8.6(4)	6.8(2)	4.5(2)	8.6(3)	7.5(2)	7.8(6)

Note. CEY = constant error in the primary movement axis, CEX = constant error in the secondary movement axis, VEY = variable error in the primary movement axis, VEX = variable error in the secondary movement axis.