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Humans vs. robots: Converting golf putter trajectories for robotic guidance

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Abstract

Robotic devices are used to provide physical guidance when teaching different movements. To advance our knowledge of robotic guidance in training complex movements, this investigation tested different kinematic data filtering methods of individual's golf putts to convert them into trajectories to be employed by a robot arm. The purpose of the current study was to identify a simple filtering method to aptly replicate participants' individual golf putter trajectories which could be used by the robot to execute them with greater consistency and accuracy than their human counterpart.

Participants putted towards 3 targets where three-dimensional data of the putter's head was filtered and then fitted by using one- or two-dimensions of the participant's putter head trajectories. As expected, both filtering methods employed with the robot outperformed the human participants in ball endpoint accuracy and consistency. Further, after comparing the filtered to the human participants trajectories, the two-dimensional method best replicated the kinematic features of human participants natural putter trajectory, while the one-dimensional method failed to replicate participant's backstroke position. This investigation indicates that a two-dimensional filtering method, using Y-forward and Z-vertical position data, can be used to create accurate, consistent, and smooth trajectories delivered by a robot arm.

Keywords: robotic guidance, physical guidance, golf putt

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1. Introduction

As technology advances, the way in which we provide physical guidance when we teach motor skills has great potential to be enhanced. Recently, robots have been used to help teach novel movements (e.g., Kümmel et al., 2014; Marchal-Crespo & Reinkensmeyer, 2008) and assist patients in rehabilitation settings (e.g., Kwakkel et al., 2008; Lugo-Villeda et al., 2009; Masiero et al., 2007). Using robots to assist with motor skill acquisition is commonly referred to as robotic guidance. Robotic guidance entails a participant being guided or moved through a specified trajectory with the use of a robotic device or manipulandum.

There are different ways to administer robotic guidance. Typically, when conducting robotic guidance investigations participants are actively involved in generating a motor plan when being guided (i.e., Active Guidance: see Bluteau et al., 2008; Kümmel et al., 2014), or do not need to generate a motor plan when being guided by a robotic device or manipulandum (i.e., Passive/Haptic Guidance: see Feygin et al., 2002). Although the robot-guided techniques currently used in the literature have had some limited success, the methods that are used are quite variable. Specifically, some of the studies that have employed robotic guidance training, have done so by implementing an ideal predetermined robot trajectory (e.g., Kümmel et al., 2014; Marchal-Crespo & Reinkensmeyer, 2008). This predetermined trajectory was programmed by the experimenters and set as the ideal trajectory to be learned by all participants. This specific type of robotic guidance has been implemented to help participants learn the optimal driving path when steering a vehicle (Marchal-Crespo & Reinkensmeyer, 2008), which is logical considering that there is a single and ideal driving path. However, robotic guidance implemented for the acquisition of motor skills should also consider the typical movement profile of the individual. Thus, more research is needed to refine guidance protocols and how they are employed to induce long lasting learning effects depending on the task being performed (e.g., Kümmel et al., 2014; Manson et al., 2014; Marchal-Crespo & Reinkensmeyer, 2008).

When administering robotic guidance, there are at least three reasons to employ each participant’s own trajectory instead of an optimal trajectory (cf. Marchal-Crespo and Reinkensmeyer, 2008). First, many research studies recruit novice participants because these individuals: a) are easier to recruit, b) are more likely to exhibit significant improvements in performance, and c) represent a relevant target population for many practical applications. On this point of expertise level, it is also known that novices typically exhibit different movement patterns than experts (e.g., expert golfers exhibit higher golf club impact velocities and more symmetric trajectories than novices: see Sim & Kim, 2010). As such, a second reason to employ individual profiles is because acquiring and filtering of each individual's trajectory also ensures that the trajectory shares spatio-temporal features of their own movement (cf., single optimal trajectory that could be perceived as more foreign or awkward). Specifically, participants should revert to their typical movement profiles upon the removal of the robotic guidance. Thus, being exposed to a "better version" of their own movements could also yield a useful contrast with unassisted practice trials and facilitate error detection processes (see details below from Bested et al., 2019a). A third reason to use each person's own trajectory can be for motivational purposes, as being told that one is exposed to an improved version of themself should yield a lower perceived task difficulty and higher perception of mastery vs. being exposed to an expert's trajectory. In our experience, participants were happy to train with the robot device when told that its trajectories were based on their own putter trajectories. In sum, while it remains to be determined if a single optimal/ expert trajectory can also elicit significant benefits; the current study ultimately employed an optimized version of each participant's own putter head trajectories because of the expertise level of the participants and our previous work.

Our laboratory has also previously used participant's individual trajectories in our robotic guidance protocols to alter the sensorimotor characteristics of upper-limb reaches in neurologically-intact participants (Manson et al., 2014). To implement robotic guidance trials successfully, Manson and colleagues (2014) used a similar protocol as employed by Bluteau, et al. (2008). To create guidance trials that were as smooth as an expert performing the movement, pre-recorded three-dimensional reaching movements to three separate targets were converted into robot trajectories. These trajectories were then used to guide participants through a rapid aiming movement to multiple target locations with or without the use of vision (i.e., variability of practice: see Shea & Kohl, 1990; Tremblay et al., 2001). Reaching movement performance was assessed prior to and after robotic guidance, and the robotic guidance practice group's performance was compared to a control group who trained unassisted. Manson and colleagues (2014) found that although both the unassisted training and robotic guidance groups improved their movement endpoint precision, only the group that trained with robotic guidance reduced their time after peak velocity and shifted toward a more bell-shaped (i.e., symmetrical) velocity profile (see Elliott et al., 2010). This change in temporal-kinematic movement characteristics, indicates that participants who trained with robotic guidance produced smoother movements. Moreover, we have also extended this robotic guidance work with a golf-putting task. Specifically, by using the 2D filtering method used in this current investigation, participants significantly improved their putting performance (Bested et al., 2019a; Bested et al., 2019b). During acquisition, it was found that combining both robotic guidance trials and unassisted trials (i.e., mixed guidance: 50% guidance group) led to a significant improvement in endpoint accuracy and precision for novice participants (Bested et al., 2019a & 2019b). Overall, it was found that by allowing participants to experience both an errorful performance (i.e., unassisted trials) and an improved version of their typical performance (i.e., robotic guidance trials), led to participants improving not only their performance during acquisition, but their ability to predict their own errors (Bested et al., 2019a; Bested et al., 2019b). From these findings, such work could be deployed with robots although the industry would likely seek to determine the simplest robot one can employ to deliver such robotic guidance protocols.

Expanding on the methodology used by Manson et al. (2014) and Bested et al. (2019a & 2019b), the purpose of the current investigation was to examine the effectiveness of two filtering methods of a single point on a golf putter head for the development of a robotic guidance protocol. That is, instead of testing different robots, we employed filtering methods that limited the physical guidance to one (1) or two (2) degrees of freedom (1DF or 2DF). That way, the same 4DF robot in our laboratory was limited to employing 1DF or 2DF only. The methodological goal was thus to develop trajectories that were smooth and accurate, but also based on the participant's natural golf putting strokes (Sim & Kim, 2010) to be used for future robotic guidance experiments. To test if the robot was successful at performing the task (i.e., putting the golf ball to the center of the target), the robot's performance was compared to the human participants putting performance. It was predicted that the robot would outperform the human participants on the golf putting task and that the two filtering methods would not differ in their performance when compared to each other. This hypothesis was made as the Selective Compliant Assembly Robot Arm used in these experiments can replicate a movement with a 0.02 mm spatial repeatability (SCARA; Epson E2L853, Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN). With this novel method of employing robotic guidance, it is hoped to change how robotic guidance is employed to facilitate the acquisition and retention of motor skills, while employing the simplest robot possible.

2. Methods

2.1. Participants

Fourteen healthy participants were recruited from the University community (7 males and 7 females; M = 26.8 yrs, range = 22 - 33 yrs). All participants were self-declared right-hand dominant and had normal to corrected-to-normal vision. Participants were questioned on their golf experience (see Appendix A: Golf Experience Questionnaire) to identify if they were novice or expert golfers. Each participant was unaware of what a golf handicap was and did not play enough organized golf to register a handicap for the golf season (i.e., which is a minimum of 5 acceptable scores: Golf Ontario, 2019). Thus, all participants in the current investigation were deemed novice golfers. Each participant signed a consent form before taking part in the experiment and the study was approved by a Research Ethics Board at the University. For participating in the study participants received payment of $10/hr for time in testing with an average testing time of 1 hour.

2.2. Apparatus

The golf putting task was executed on a putting green (BirdieBall Putting Green, BirdieBall Inc., Wheat Ridge, CO, USA) measuring 488 cm long × 122 cm wide. During the task, participants putted to three custom built circular Light-Emitting Diode (LED) targets starting from an LED home position (see Figure 1). The LED targets were constructed with 8 bright white circular LEDs (i.e., 2 mm in diameter), which represented the circumference of a golf hole measuring 10.8 cm in diameter. Three targets were located 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). The targets were spaced at 10% of total amplitude (i.e., at 21 cm intervals) to ensure that they were of perceivably different amplitudes (re.: Weber's Law see: Gescheider, 1997). In addition, the LEDs were inserted under the putting green to guarantee that the targets were only perceivable when lit and so that they did not interfere with the roll of the golf ball. The targets and home position for the ball were 52 cm from the right edge of the putting green. To ensure a consistent start location for the ball on every trial, a home position marker was used. A protective cage (L: 193 cm x W: 208 cm x H: 202 cm: see Figure 1) hovered over the left side of the putting green (i.e., see Figure 1). This cage separated and protected participants from the Selective Compliant Assembly Robot Arm used for robotic guidance trials (SCARA; Epson E2L853, Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN). The robot arm used in the current experiment could move in up to four degrees of freedom (i.e., “sway”: left and right movement along the X-axis, “surge”: forward and backward movement along the Y-axis, “heave”: up and down movement along the Z-axis, and yaw: rotation around the Z-axis) and replicate a movement with a 0.02 mm spatial repeatability. An opening in the protective cage was built to allow the robot to be used during the golf putting task. An extension of the cage ensured that participants and the experimenter did not come in direct contact with the robot (L: 48 cm x W: 208 cm). Each golf putt was performed using 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). For robotic guidance trials, a second identical putter was connected to the robot using a custom-built connection with the golf putter head as well as a grip connection to the cage so the robot could putt without any human assistance (see Figure 1).

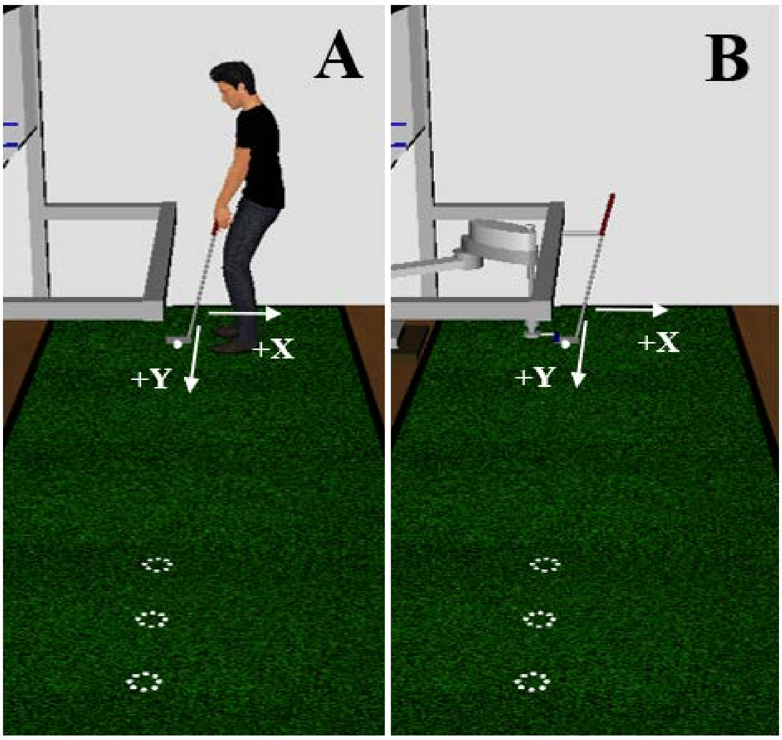

Figure 1. Rendering of the experimental set-up. A: Human putting trials. B: Robot putting trials. Kinematic data of the putter was recorded by using an Optotrak motion capture system, which was mounted on a custom-built stand on the right side of the putting green.

2.3. Task and procedure

The task required participants to perform a golf putt to three different targets. This golf putting task, unlike a traditional golf putt, required participants to try their best to have the ball stop on the center of the target, as opposed to sinking it in a hole. Thus, this putting task required more distance control to ensure that the ball did not go past the hole. This task was chosen so that it would not only focus on distance control of a golf putt but also so that we could switch between targets in future investigations in a random order. Using a typical golf hole would not allow us to have participants putt to different targets one after another without a significant increase in time (i.e., removing and inserting a hole cover) as well as the interference this would cause with other golf putts performance from the holes not aligning perfectly with the surface. At the start of each trial, the home position and a target were presented. Participants were instructed to stand with their feet shoulder width apart with the ball in the center of their stance and to grip the putter with a standard overlapping putter grip. Participants were then asked to place the putter as closely behind the golf ball as possible in addition to aligning the middle of the putter head with the middle of the golf ball. When ready to execute the golf putt, participants were then instructed to focus on the target that was presented for that trial.

After the experimenter ensured that the participant was in the correct stance and with the putter in the relatively correct location, the trial began. The beginning of each trial was signaled by a double beep sounded by a piezo-electric buzzer (Mallory Sonalert Products Inc.: Model SC628, tone frequency of 2900 Hz). Following the double beep, participants were asked to shift their focus of attention from the target onto the golf ball and prepare to execute the golf putt to the target displayed. Following a two second delay, a third beep sounded instructing participants to initiate their putt. Three seconds were given to complete a single putt (i.e., backstroke and forward stroke) before a fourth and final beep sounded ending the trial.

The experiment consisted of one testing phase where participants (i.e., both human and robot participants) performed putts to each of the three targets in a blocked fashion. The orders of the blocks were presented in a counterbalanced fashion. Each block consisted of 5 familiarization trials followed by 10 trials in the testing phase. Participants completed a total of 45 trials (i.e., 15 familiarization and 30 testing trials).

2.4. Filtering methods

Three trajectories unique to each participant (i.e., averaged across the 10 trials performed for each target) were programmed into the robot. Participant's three-dimensional putts were recorded at 250 Hz using an infrared emitting diode (IRED) secured to the inside front edge of the putter head. The IRED was monitored by an Optotrak Certus motion capture system (Northern Digital Inc., Waterloo, ON, Canada). The start and the end of both the backstroke and forward stroke of the golf putt were identified when the putter head velocity rose above and fell below 30 mm/s for 3 consecutive samples. To ensure the robot trajectories most resembled human participants putting trajectories, two different filtering methods were used and tested by the robot.

Specifically, both a one-dimensional (1D) and a two-dimensional (2D) filtering method were employed. The purpose of using two filtering methods was to determine if such simple methods of controlling different degrees of freedom of the trajectory can successfully yield putting trajectories that either: A) replicated the amplitude of the putter trajectory while constraining the movement direction and elevation (i.e., 1D method), or B) replicated both amplitude and elevation of the putter trajectory while constraining the movement direction (i.e., 2D method). Also, using 1D and 2D filtering methods were expected to help determine if a 1D or 2D robot could be employed in future applications. Further, the procedures used by Manson et al. (2014) were incorporated in the current investigation, so that participants could eventually train using a smoother version of their own trajectories implemented by a robotic device. Both filtering methods led to smooth trajectory data that were converted into robot trajectories and compared to the kinematic trajectories produced from human participants. This comparison was done to ensure that the replication of the golf putter trajectory was successful.

To create the trajectory for each target, each participant's backstroke was first identified from the start position and end position of their average putter trajectory for the respective target. The data points were then taken from the backstroke (e.g., 0 → -20 cm backwards in the primary movement axis: Y) and doubled (e.g., backstroke = 0 → -20 cm, forward stroke = -20 → +20 cm) to create the forward stroke of the putting stroke (1D Filtering Method). The distance of the backstroke was the main measure as this has been identified as an important kinematic factor for distance control of a golf putt (see Delay et al., 1997). Another reason why the back stroke was doubled and used for the forward stroke was to ensure that at ball impact (i.e., crossing of the starting position) occurred at peak velocity. Contacting the ball at approximately peak velocity resulted in smoother acceleration and deceleration of the robotic device. Once this new trajectory was created, a 30th-order polynomial was fitted with a custom MATLAB script (using the Polyval and Polyfit functions in the curve fitting toolbox: The MathWorks Inc., Natick, MA, USA: see Manson et al., 2014). The custom script was used to create a trajectory that was in equal length to the back stroke and to create a smooth putting stroke to be used by the robot. The 30th-order polynomial was used as this method of filtering human participants' limb trajectory had been used in prior experiments conducted in our lab (see Manson et al, 2014). Once the polynomial fit was applied, the trajectory was further filtered using a low-pass Butterworth filter [10 Hz] to further increase the smoothness of the trajectory. Once filtered, the new trajectory was also separated into the two different movements (i.e., backstroke and forward stroke) and converted into coordinates that could be reproduced by the robot.

Once these coordinates were created, the peak velocity and peak acceleration values were scaled to ensure participants' putts with the robot were successful (i.e., stopped on or just beyond the hole consistently). The scaling was done so that the robot could be incorporated using participants' kinematic trajectories for future robotic guidance studies. Although the scaling was done successfully for the given experiment, the current methodology was limited by the size of the room and the robot's physical limits in movement (i.e., both amplitude and velocity). The robot arm was controlled using a custom SPEL + program (Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN) interfacing with MATLAB (The MathWorks Inc., Natick, MA, USA), which ran the entire experiment with custom scripts. The robot then performed the same putting task as performed by the human participants using the 2 filtering methods. The robot's performance as well as kinematic data was then compared to that of the human participants performance to not only demonstrate that the robot was more accurate at performing these movements, but also to ensure that the filtering method matched the human participants putter trajectories.

2.4.1. 1D Filtering method (Y axis)

To ensure optimal contact with the ball, participants putting strokes were constrained to constant X (i.e., secondary axis: left and right) and Z (i.e., tertiary axis: up and down) values.

This resulted in the putter head trajectory movement that was constrained in all 4 axes of the robot (i.e., sway, surge, heave, and yaw) with a specific backstroke and forward stroke unique to each individual participant (i.e., Y axis).

Once these robot trajectories were created for each participant, the robot reproduced the human participants putter trajectories. Although this filtering method produced movements that could be replicated by the robot, 3 participants' trajectories were unable to be used. This was because these participant's trajectories were much shorter in the Y axis and without the tertiary axis (i.e., Z axis) included, the trajectory processing resulted in a significant shortening of the backstroke which did not allow the robot to effectively execute the participants' putts (i.e., accelerate fast enough to hit the ball to the target). As a result, these participants data were removed from the putter head kinematics analyses. Although this was the case, this was due to the robot's acceleration limits (i.e., 2,500 mm/s^2).

2.4.2. 2D Filtering method (Y and Z axis)

Participants' putter trajectories were aligned from the start position and were averaged for both the primary movement axis (i.e., Y) as well as the tertiary movement axis (i.e., Z). This allowed for a trajectory that better replicated each participant's putter trajectory (see Figures 2 and 4). To create the trajectory for each target, the backstroke as well as the forward stroke were identified based on the start position and end position of each stroke (similar to the 1D filtering method). The entire stroke was used and replicated as participants tended to reach peak velocity of the forward stroke at ball impact (see Table 1). This finding corresponds with the study conducted by Sim and Kim (2010), which also showed that novice participants golf strokes typically are symmetrical in that participants reach peak velocity in the middle of their forward stroke (i.e., ball impact: see PVPos in Table 1). Once this new trajectory was created, the same procedures were used to fit and filter the trajectory as used in the 1D filtering method but for both the primary (i.e., Y) and tertiary movement axes (i.e., Z). To ensure perfect contact with the ball was made, participants' putter trajectories were fitted to a constant secondary axis (X or left and right direction).

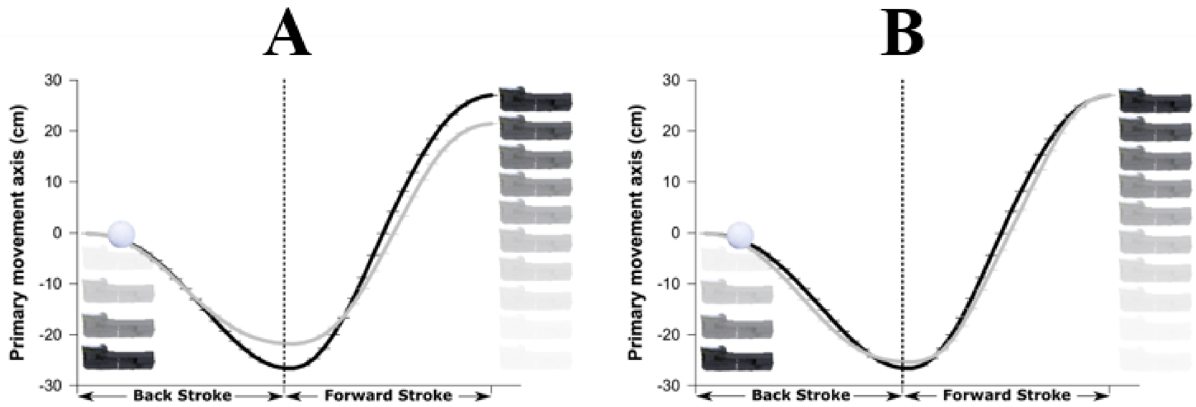

Figure 2. Examples of one participant’s averaged trajectory (i.e., backstroke and follow through in the primary movement axis [Y]: black line) with both filtering methods used with the robot (i.e., grey line). On the edges of each panel, a trail of golf putter heads depict the backstroke and forward sub-segments of the stroke. The putter head changes from light grey to solid black to depict from the start to the end of each sub-segment. A: 1D Filtering Method, B: 2D Filtering Method.

2.5. Data analyses

Performance data (i.e., ball endpoint location) was recorded with the use of a grid system (see Figure 3). This 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 (i.e., A position: see Figure 3). From there, each line away from that position was 30 cm apart in the primary direction (positive on the Y-axis A - O: see Figure 3). Similarly, the secondary movement axis (i.e., X-axis) started from the left side of the putting green (i.e., when facing the participant; 1 position: see Figure 3). The large grid ball endpoint location was recorded in MATLAB and stored for later analyses (e.g., J2 = 270 cm Y-axis, 30 cm X-axis: see Figure 3). To determine where the ball landed specifically within the identified square, a 30 cm ruler was aligned to the edge of each square by the experimenter to calculate the position in which the ball was located within the specified square (e.g., Y = 20, X = 20 cm). These values were again recorded in MATLAB, which yielded the location of the center of the ball on the green, to the nearest millimeter (e.g., Y = 290 cm, X = 50 cm). This ball endpoint location was then used to subtract the target location resulting in a signed error measure.

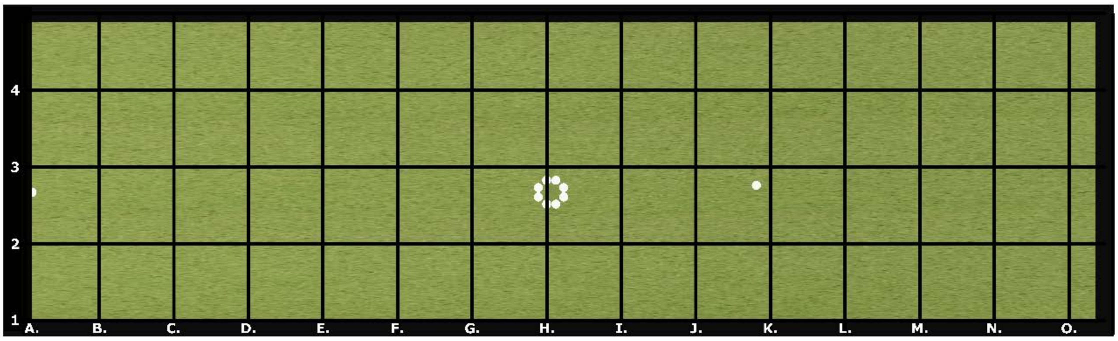

Figure 3. Depicting the process of collecting the ball location on the putting green. A) Once the ball had been putted by participants the large grid location was input into the MATLAB program (e.g., J2). B) Once the large grid location was input, participants ball location within the specified square was measured with the use of a ruler for each axis. The custom MATLAB program then calculated the exact location of where the ball was on the green which was used for all performance measurements.

2.5.1. Ball endpoint measures, putter head kinematics, and analyses

The ball endpoint measures consisted of constant error (i.e., signed average of ball endpoints) in the primary movement axis (CEY) and secondary movement axis (CEX) as well as variable error (i.e., standard deviation of ball endpoints) in the primary movement axis (VEY) and secondary movement axis (VEY), respectively. As the main objective was to identify if there was a difference between the three conditions (i.e., humans, 1D, and 2D), the target data was collapsed within each condition yielding one overall result for each variable investigated. Ball endpoint measures were analyzed using three independent sample t-tests, to assess the differences between the three conditions (i.e., humans, 1D, and 2D). Independent sample t-tests were used because of the human participants performance data being compared to the robot's performance. These were deemed as independent groups as a result of the robot's performance capabilities (i.e., 0.02 mm spatial repeatability: SCARA; Epson E2L853, Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN) which is independent to what can be produced by a human participant and even an expert golfer (i.e., SD = 8 mm, backstroke amplitude for a 2 meter putt: see Delay et al., 1997).

To ensure that the filtering of the trajectories was representative of participants' golf putts, putter head kinematic measures of participants putter end position of the backstroke

(BackPos) as well as participants putter position at peak velocity of the forward stroke (PVPos) were taken from the position data of both human participants and robot filtering methods (i.e., 1D and 2D) in the primary movement axis (i.e., Y). These two (2) unique elements of each trajectory were first selected to yield the lowest number of variables to eventually employ in practical applications. The decision to take BackPos and PVPos was also based on evidence that modelling a trajectory based on positions achieved at peaks and troughs of a velocity profile can suffice to model entire limb trajectories (see Figure 21 as associated text in Rosenbaum et al., 1995). Also to further investigate how well trajectories matched their robotic counterpart, Root Mean Square Error (RMSE) was computed between the average normalized Human, 1D and 2D Filtering Methods putter head trajectories for each of the axes of interest (i.e., X & Y: see Table 2). Finally, as the main objective was to identify if there was a difference between the three conditions (i.e., humans, 1D, and 2D), the target data was collapsed within each condition yielding one overall result for each variable investigated. Trajectory variables were analyzed using three paired sample t-tests to assess the differences between the conditions (i.e., humans, 1D and 2D). A paired samples t-test was conducted because of comparisons being made between participants own putter trajectories (i.e., human) and their own robot filtered trajectories (i.e., 1D and 2D method). Cohen's d was also calculated for all significant effects in order to determine the effect size (i.e., reported as dz).

A Bonferroni correction (i.e., $\alpha_{corrected} = .05/3 = .016$) was applied to correct for the three t-tests conducted for each variable. Means and between-subject *SDs* were reported in Table 1 and Table 2. If variance was not equal between conditions, the correction of equal variances not assumed was applied (i.e., Levene's Test for Equality of Variances).

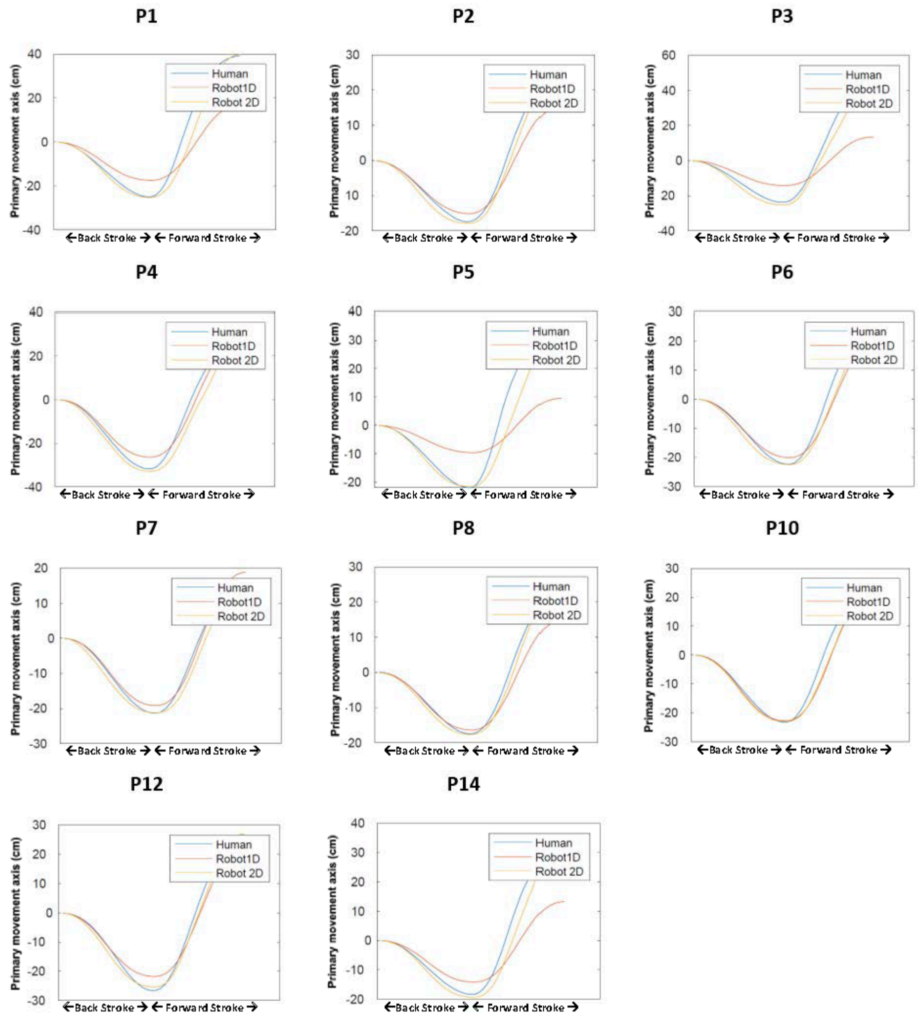

Figure 4. Participants' averaged trajectories (i.e., backstroke and follow through in the primary movement axis [Y in cm]), with both filtering methods used with the robot.

Table 1

Means and between-subject SDs for the ball endpoint measures and putter head kinematic measures for all conditions: Humans, 1D Filtering Method (1D), and 2D Filtering Method (2D).

	Humans	1D	2D
CEY (cm)	24.4 (25)	0.1 (2)	1.3 (3)
CEX (cm)	1.7 (3)	1.7 (1)	2.0 (1)
VEY (cm)	55.0 (22)	2.0 (1)	2.1 (1)
VEX (cm)	5.1 (2)	1.1 (0.3)	1.0 (0.5)
BackPos (cm)	-23.0 (4)	-17.0 (5)	-23.0 (4)
PVPos (cm)	-0.2 (5)	0.4 (1)	1.2 (4)

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, BackPos = putter end position of the backstroke, and PVPos = putter position at peak velocity of the forward stroke.

Table 2

Means and between-subject SDs of Root Mean Square Error (RMSE) computed between the average normalized Human, 1D and 2D Filtering Methods putter head trajectories for each of the axes of interest (i.e., X & Y).

	Human/1D	Human/2D
RMSEy (cm)	6.7 (4.8)	3.1 (1.3)
RMSEx (cm)	0.64 (0.5)	0.65 (0.5)

Note. RMSE = root mean square error for each of the axes of interest (i.e., X & Y).

3. Results

3.1. Ball endpoint measures

3.1.1. Humans vs. filtering methods

Analysis of ball endpoint CEY when comparing human participants to the 1D filtering method, $t(41.9) = 6.4$, $p < .001$, dz = 1.01, and the 2D filtering method, $t(41.9) = 6.1$, $p < .001$, dz = 0.93, revealed that both robot filtering methods were more accurate than human participant performance. Analysis of CEY when comparing the 1D filtering method to the 2D Filtering Method yielded no significant differences between the methods, $t(73) = -2.0$, $p = .046$. Analysis of CEX yielded no significant differences when comparing between human and robot performance (*p's* > .30).

Analysis of ball endpoint VEY when comparing human participants to the 1D filtering method, $t(41.2) = 15.6$, $p < .001$, dz = 2.46, and 2D filtering method, $t(41.1) = 15.6$, $p < .001$, dz = 2.43, revealed that human participants were significantly more variable than both robot filtering methods. Analysis of VEY when comparing the 1D filtering method to the 2D Filtering Method yielded no significant difference, $t(53.9) = -0.7$, $p = .52$.

Analysis of ball endpoint VEX when comparing human participants to the 1D filtering method, $t(43.2) = 11.2$, $p < .001$, dz = 1.94, and 2D filtering method, $t(45.3) = 11.3$, $p < .001$, dz = 1.70, again revealed that human participants were less precise than the robot. Analysis of VEX when comparing the 1D filtering method to the 2D Filtering Method yielded no differences between the methods, $t(70.4) = 1.1$, $p = .26$.

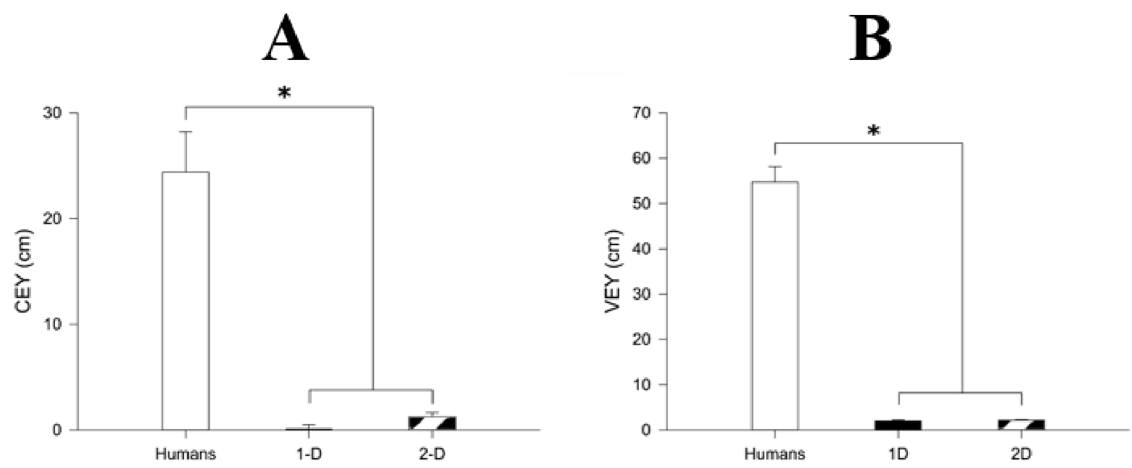

Figure 5. A: Constant error in the primary movement axis (CEY), B: Variable error in the primary movement axis (VEY) for each condition (i.e., humans, 1D, and 2D) collapsed across all targets. *Note.* Between-group differences were reported with a (✱) identifying significant differences between both Filtering Methods (i.e., 1D & 2D) when compared to human participants. Error bars represent the standard error of the mean.

3.2. Putter head kinematic measures

3.2.1. Humans vs. filtering methods

Analysis of BackPos when comparing the 1D filtering method to the human participants, $t(32) = -8.7$, $p < .001$, dz = 1.14, and 2D filtering method, $t(32) = 8.4$, $p < .001$, dz = 1.12, revealed a significant difference between conditions. This result indicated that the 1D method had significantly smaller BackPos amplitudes when compared to the human participants trajectories and the 2D filtering method. Analysis of BackPos when comparing Human participants to the 2D filtering method did not yield a significant difference, $t(32) = -0.4$, $p = .73$. The analysis of PVPos yielded no significant differences (*p's* > .25).

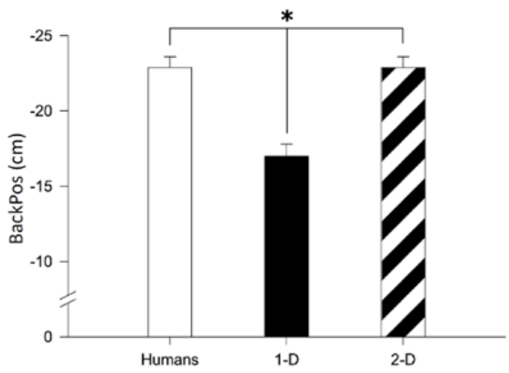

Figure 6. Putter head position at the end of the backstroke (BackPos) for each condition (i.e., Humans, 1D, & 2D). *Note.* Significant differences were reported with a (*). Error bars represent standard error of the mean.

Root Mean Square Error (RMSE) was computed between the average normalized Human and 1D Filtering Method putter head trajectories for each of the axes of interest (i.e., X: M = 0.64 cm, SD = 0.5 cm and Y: M = 6.7 cm, SD = 4.8 cm). The RMSE was also calculated between the average normalized Human and 2D Filtering Method putter head trajectories for each of the axes of interest (i.e., X: M = 0.65 cm, SD = 0.5 cm and Y: M = 3.1 cm, SD = 1.3 cm). A paired samples t-test was conducted identifying a significant difference between the filtering methods in the Y axis, $t(10) = 2.9$, $p = 0.015$ confirming that the Y axis was a better fit for the 2D Filtering Method (RMSE = 3.1 cm) when compared to the 1D Filtering Method (RMSE = 6.7 cm).

4. Discussion and Conclusions

The current investigation tested a novel and simple method to collect and filter individual's golf putter trajectories and trajectories capable of successfully performing a unique golf putter trajectory using limited to only 1 or 2 degrees of freedom (i.e., 1D & 2D). As predicted, both filtering strategies used to create ideal robot trajectories performed by the robot outperformed the human participants in the golf putting task (i.e., in CEY, VEY & VEX). The robot stopped the ball on the hole on average and did so with much greater consistency compared to the original human performance.

Although both filtering methods used successfully converted human participants data into robot coordinates, the 1D filtering method was unable to be implemented by the robot for 3 participants. Specifically, trajectories from 3 participants were not properly translated to the guidance protocol because of the shortness of the participants' backstrokes. This was because these participant's trajectories in the Y axis were short to begin with and removing the tertiary axis (i.e., Z axis) resulted in further shortening of the backstroke. Further, as a result of the backstroke being shortened, unfortunately due to the robot's acceleration limitations (i.e., maximum acceleration of 2,500 mm/s^2) the 3 participants trajectories were not able to be used. This was demonstrated when investigating participants putter end position of the backstroke as the 1D filtering methods backstroke position was statistically shorter when compared to both the human participants and the 2D filtering method accordingly. One reason as to why the 2D filtering method was able to use all participants trajectories may have been because of the second dimension included (i.e., z-axis: heave) which resulted in movements that replicated participants' putting performance more precisely and allowed the robot more time to accelerate the club head. Although these differences did emerge for the putter end position of the backstroke, no differences were present in the putter position at peak velocity of the forward stroke.

Recently, we have shown that incorporating the 2D filtering method has led to the successful implementation of robotic guidance for improving putting performance (Bested, et al., 2019a; Bested et al., 2019b). Specifically, combining both robotic guidance and unassisted trials (i.e., mixed guidance: 50% guidance group) during the acquisition phase of a learning paradigm led to a significant improvement in endpoint accuracy and precision for novice participants (Bested et al., 2019a). Further, these results were replicated, and it was found that robotic guidance may influence participants performance during motor skill acquisition (Bested et al., 2019b). By allowing participants to experience what both an errorful performance (i.e., unassisted trials) and an expert performance (i.e., robotic guidance trials) felt like (i.e., mixed guidance), we found that participants improved not only their performance during acquisition, but their ability to predict their own errors (Bested et al., 2019a). Critically, our approach in the current study and our previous work has employed guidance that brings the participant to a unique but optimal version of their own trajectories and induced significant motor learning effects, only when combine with unassisted practice. However, we also ought to raise the issue of exploring different movement patterns to optimize motor learning.

Many researchers have previously attempted to employ robots to deliver optimal trajectories, which has been met with quite mitigated success (e.g., Reinkensmeyer et al., 2004). Moreover, some have even suggested that employing robots to perturb limb trajectories might be more effective than guiding trajectories. That is, perturbing the participant's limb away from a desired trajectory may yield greater motor learning effects than guiding the participant's limb towards a trajectory (i.e., error-augmenting vs. error-reducing guidance: see Lee & Choi, 2010). For example, it has been shown that motor learning can be facilitated only when the participant deviates from the optimal trajectory (e.g., Williams et al., 2016) or only when the participant makes a common error (i.e., error-field guidance: see Patton et al., 2022). In contrast, our anecdotal laboratory experience is that participant's motivation is high when helped towards an optimal trajectory, whereas many individuals find the trajectory disruptions frustrating. As such, while we acknowledge an entire field of research challenging the use of error-reducing guidance per se, our previous work has shown that mixing such guidance with unassisted practice has yielded significant, relatively persistent, and transferable improvements in golf putting performance. Indeed, incorporating the filtering method used in the current investigation has led to the development of effective robotic guidance based on participants individual trajectories, that can also be easier to multiply and deploy than more complex guidance systems.

As demonstrated, using 1D and 2D filtering methods to translate participant's trajectories to robotic guidance protocols is effective for improving the participant's motor learning in a golf putting task (Bested et al., 2019a; 2019b). However, the current investigation and the ones conducted using this filtering technique have done so with a robot that has 4 degrees of freedom, high torque motors, and precise position controllers. Although successful, using a robotic device with this capacity is highly expensive. To reduce the cost of running such a training protocol, we plan to conduct similar investigations by implementing robots that move in only 2 degrees of freedom (i.e., x-axis: left and right, y-axis forward and backward). Although in the current investigation the 1D Filtering Method produced guidance trajectories that were significantly different to the participants' own trajectories (i.e., y-axis forward and backward), this did not yield an increase in error in this axis. Limiting the amount of axes used to only 1 is consistent with previous research identifying that it is important to constrain and reduce variability in order to produce successful performance (see Todorov, 2004). This type of performance constraint is relative to the current task being performed as it has been identified that putting to targets differing in distance, was dependent on the amplitude of the backstroke (see Delay et al., 1997; Sim & Kim, 2010). Although it may be cost effective to run this protocol with a more simplistic robot, it is unknown as to whether constraining these other kinematic dimensions will have similar effects on motor learning and task performance. It may be the case that if this robotic guidance is performed with a robot that is unable to provide the participant with a natural feeling golf trajectory, that it may not help participants improve their putting performance accordingly. Further investigations are needed to investigate these areas of research.

Overall, the present study demonstrated a novel way to collect, filter, and convert individual participant's golf putts into robot trajectories capable of producing highly consistent, accurate golf putts. Although both filtering methods were successful, the 2D filtering method used was the best at replicating participants individual trajectories. Due to the success of the current investigation, the current methodology has been implemented in experiments investigating the influence of robotic guidance on the learning of a complex novel golf putting task (Bested et al., 2019a; 2019b). Further investigations are needed to understand further as to what degrees of freedom are necessary to promote effective motor learning of a golf putting task.

5. Declarations

Acknowledgements

None of the experiments were preregistered. Data are available upon request. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee. The study was approved by the Research Ethics Board at the University of Toronto (Protocol Reference #34147).

None of the experiments were preregistered. Data is available upon request.

Conflicts of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Appendix: Golf Experience Questionnaire

1. What is your age? ____

2.
A. Have you ever completed a full 18 hole round of golf before and/or mini putt?
- Golf
- Mini Putt
- Both

B. If yes, how old were you when you completed your first round?
Golf ____Mini Putt ____

3. In the past year, how many rounds have you completed?
Golf ____Mini Putt ____

4. What is your handicap (if known)?
Golf ____Mini Putt ____

Adapted with permission from Prof. Joe Baker's master's athletes survey, which was retrieved at https://www.yorku.ca/bakerj/mcmaster_golf_questionnaire.htm on February 3, 2017.