Reward-Based Sensorimotor Decision Making

by:

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ABSTRACT

Existing theories suggest that evidence is accumulated before making a decision with competing goals. In motor tasks, reward and motor costs have been shown to influence the decision, but the interaction between these two variables has not been studied in depth. A novel reward-based sensorimotor decision-making task was developed to investigate how reward and motor costs interact to influence decisions. In human subjects, two targets of varying size and reward were presented. After a series of three tones, subjects initiated a movement as one of the targets disappeared. Reward was awarded when participants reached through the remaining target within a specific amount of time. Subjects had to initiate a movement before they knew which target remained. Reward was found to be the only factor that influenced the initial reach. When reward was increased, there was a lower probability of intermediate movements. Both target size and reward lowered reaction times individually and jointly. This interaction can be interpreted as the effect of the expected value, which suggests that reward and target size are not evaluated independently during motor planning. Curvature, or the changing of motor plans, was driven primarily by the target size. After an initial decision was made, the motor costs to switch plans and hit the target had the largest impact on the curvature. An interaction between the reward and target size was also found for curvature, suggesting that the expected value of the target influences the changing of motor plans. Reward, target size, and the interaction between the two were all significant factors for different parts of the decision-making process.

DEDICATION

In loving memory of Katie Conrad. Katie was a fantastic leader and offered invaluable wisdom to me during my first week as a freshman.

ACKNOWLEDGEMENTS

I would like to acknowledge Dr. Justin Fine for his tremendous efforts in the creation and refinement of the scientific question, guidance in programming the experiment, and knowledge and assistance in the data analysis. His advanced knowledge in coding and statistical analyses greatly improved my understanding of the topic in addition to the development of these skills. This work would not have been completed without his help.

I would also like to recognize Jacob Schuler, Michael Ruta, and Archana Mysore for their help during data collection. Having their assistance was crucial to collecting data from subjects in a timely manner. A special thanks is given to Jacob and Michael for teaching me how to setup the EEG system.

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INTRODUCTION

Each day, people make a multitude of decisions, each with varying levels of risk. Some decisions must be made among a finite number of competing options. People will often make decisions between options based on value. Reward and cost are two main factors that influence the perceived value of an option. How reward and cost are integrated into the decision can give insight to the preferences of competing options. Economists have been studying this interaction for decades (Edwards, 1954; Tversky and Kahneman, 1986; Gonzalez et al., 2005) to investigate how economic decisions are made. Studying the mechanism behind how reward and cost are integrated during the decision-making process for other types of decisions is often overlooked and may elucidate the interaction of reward and cost.

When studying value-based decisions, previous studies have typically manipulated the costs associated with the competing options (Tversky and Kahneman, 1986; Gonzalez et al., 2005). This cost is probability that an event will occur and is usually compared to a sure option (100% probability of occurring). The decisions show how much risk people are willing to take over a safer option, which gives insight to how reward and cost interact. Reward has also been manipulated, and typically this is done in one of two ways. The first way is adjusting the reward with respect to the costs so that the competing options have similar expected values (probability of occurrence multiplied by the reward). The other way reward is typically manipulated is by changing the reward from a gain to a loss (Tversky and Kahneman, 1986). It was shown that losses are processed differently than gains. Researchers have recently begun studying decision-making during motor tasks to determine if the same principles apply to decisions involving motor planning and control. In sensorimotor decisions, losses and gains were shown to be processed differently as well (Chapman et al., 2015). However, there was a difference between economics and motor decision-making in an equivalent task (Wu et al., 2009). Several reviews have addressed the gaps between economic and sensorimotor decision-making (Pessiglione et al., 2018; Wispinski et al., 2018; Wong et al., 2015; Körding and Wolpert, 2006; Gallivan et al., 2018; Wolpert et al., 2011). However, it is still unknown why economic and sensorimotor decision-making processes differ.

For some motor tasks, people must decide how to begin a movement when they are unclear of the goal. When there is uncertainty, an intermediate movement between the competing goals can occur (Haith et al., 2015; Christopoulos et al., 2015; Christopoulos et al., 2017). An intermediate movement is favorable because more evidence can be accumulated (Chapman et al., 2010; Wong and Haith, 2017; Haith et al., 2015; Christopoulos et al., 2017; Wiener et al., 2009; van den Berg et al., 2016; Glaze et al., 2015; Velanova et al., 2007). Evidence is collected until a threshold is reached for one of the goals, which is when the decision is made. Factors such as target separation (Wong and Haith, 2017) have been manipulated to show that intermediate movements were not used with some motor contingencies. There has been no work done assessing how motor costs and reward are integrated during a motor task where a movement must be made when the goal is still unclear. Additionally, motor contingencies in these types of tasks have not been scaled to the subject. The only known scaling to the individual subject was done in a task with only one goal, but not competing options (Trommershäuser et al., "Statistical Decision Theory and Tradeoffs in Motor Response," 2003; Trommershäuser et al., "Statistical Decision Theory and Rapid, Goal-Directed Movements," 2003).

In the present study, a novel reward-based decision-making task was developed to assess how reward and target size affect and possibly interact to influence the decision during a motor task with unclear, competing goals. Subjects were presented two possible targets and initiated a movement shortly after a series of three beeps. One target disappeared after the third beep, creating a go-before-you-know paradigm (Chapman et al., 2010). Targets varied in size (scaled to each subject) and reward, and subjects performed ballistic reaches through targets. Previous studies have only manipulated one factor, either reward or motor costs (e.g. target size, target separation, perturbations, etc.). The order in which the factors are changed could have an effect. In neuroeconomics, it was found that decisions are affected by a change in the presentation of the decision. Changing the way a decision is presented, such as a loss or a gain, has an effect on decisions (Tversky and Kahneman, 1986; Loewentein and Prelec, 1992; Gonzalez et al., 2005; De Martino et al., 2006). It was discovered that when a question is framed as a loss, people are more likely to pick the "risky" option when compared to a question framed as a gain (Tversky and Kahneman, 1986; Gonzalez et al., 2005). The order of information (reward first or target sizes first) was manipulated to control for a possible framing effect.

It was hypothesized that there would a lower chance of intermediate movements only when the reward difference between two possible targets is increased, suggesting that reward influences the initial decision the most. It was hypothesized that both target size and reward would have an effect on reaction times, suggesting that both characteristics of the target influence the decision. Since it was hypothesized that there would be a lower chance of intermediate movements when the reward is increased, it was further hypothesized that curvature of the trajectory would increase as well. This is because there is more of a correction required than an intermediate movement. Ergo, reward would be driving both the initial decision and the changing of motor plans, but motor costs would still be considered during the decision-making process.

METHODS

Participants

Thirty-two right-handed (self-reported) participants (22 males; mean age ± SD: 22.8 years ± 4.0) with no neurological disorders were recruited. All participants were naïve to the purposes of the study and provided written informed consent prior to testing in accordance with the Declaration of Helsinki. Subjects were paid $25 for participating in the experiment. The experimental protocols were approved by the Arizona State University Institutional Review Board.

Apparatus

Participants were seated in front of a robotic manipulandum with a horizontal glass table blocking the view of their arm. An LCD monitor (60 Hz refresh rate) displayed the targets and the cursor onto a mirror placed horizontally above participants' arms. Subjects were asked to make ballistic reaches through targets distributed in the horizontal plane while grabbing the handle of a robotic manipulandum (KINARM, BKIN Technologies) with their right hand. The robotic manipulandum was used to track and record hand kinematics.

Pilot study

A pilot study (6 subjects; 3 males, 24.2 years ± 5.8) was performed to determine the parameters that would make the task challenging yet motivating and feasible. These parameters were used for one experiment (see below). It was found that several parameters needed adjustment. Changes between the Pilot Study and Experiment are noted in the "Changes from Pilot" section.

Experiment 1: Training

All subjects participated in a training block of 100 trials lasting approximately 10 minutes before beginning Experiment 2 (below). Subjects were instructed that three tones would be presented. On the first tone, no information about target size or location was provided. On the second tone, one target was displayed. The target size could be small or large (radius = 1.5 or 3 cm, respectively) and could appear on the left or right of the start position (± 22.5° relative to straight ahead). Target sizes and locations were randomized across trials. On the third tone, subjects were instructed to reach through the target within 550 ms from the tone (Fig.1, row 1).

Visual feedback in the form of the target turning green and an image of a mascot was presented to subjects when the target was hit successfully. The target did not turn green on unsuccessful trials and no mascot was presented. The purpose of the training was to familiarize participants with the task and have them practice movement initiation within the specified time after the third tone. Data from this training block was analyzed to calculate the target sizes for Experiment 2 (see below).

Experiment 2

Twenty-six participants (19 males; 22.4 years ± 3.5) were recruited and were asked to perform a ‘shooting’ task through targets 45° apart (± 22.5° relative to straight ahead from the starting hand position) and 15 cm away radially from the starting position. Subjects were required to position the cursor in a starting target (1-cm radius) to begin each trial. Once the cursor was in the starting target, the target would change from red to green. After 500 ms, a series of three audible tones were played, at an inter-tone interval of 750 ms (Fig. 1). Subjects were instructed to start the movement as soon as they heard the third beep. After hearing the first tone, either the two targets (pink circles, Fig. 1, row 2) or the reward values (numbers, Fig. 1, row 3) were displayed, and subjects were instructed to remain in the starting position. At the second tone, the second cue was displayed: the target reward values or the target sizes (see Experiment 1, Fig. 1, rows 2 and 3). At the third tone, only one of the two targets, together with its reward value, were displayed. Subjects were required to initiate the ‘shooting’ movement within 200 ms after the third tone and move the center of the cursor through the target. Once the movement was initiated, participants had 350 ms to move through the target to receive the reward. On successful trials, subjects were rewarded with a green target and points towards a cumulative score. After each trial, the score was displayed for 750 ms. If movement was not initiated within 200 ms of the third tone, the trial was not successful and a “Too slow” message was displayed on the screen. If a target was not hit within 350 ms after movement, subjects were not rewarded with a green target. Subjects were not penalized for missing the target. Only the inner target (pink circle) could be hit to receive reward. For about 8% of the trials, the two targets remained after the third tone and subjects were able to reach through the target of their choice (*Free Choice* trials). The remaining trials (~92%) were *Forced Choice*, where only one target remained after the third tone. Subjects were notified with on-screen text before each block began. The side in which the target would remain after the third tone on Forced Choice trials was counterbalanced across trials. The outer radius of both targets (red circles, Fig. 1) was the same (4.1 cm) across target sizes. The inner target radii were determined from each subject's variability during the training phase (see Target Size Determination section below). Target sizes were selected such that there was either a 50%, 70%, or 90% chance of hitting the target within the above-describe time constraints. These probabilities were based on individual subject's performance variability. There were five different possible inner target radius ratios of the left target to the right target: 50:50, 50:70, 50:90, 70:50, and 90:50. Differences in reward between the left and right target were as follows: ± 5 and ± 2 points. The average trajectories for the conditions shown in Fig.1 for an example subject are shown in Fig. 2. A total of 1040 trials (across 11 consecutive blocks) separated into blocks of 160 Forced Choice trials and 16 Free Choice trials were performed in approximately 1.3 hours (Fig. 3). Target sizes and reward values were randomized within each block of Force Choice trials.

Target Size Determination

Data from the training block were used to determine the target sizes such that, for each subject, there would be a hit probability of 50%, 70%, and 90% given their individual motor variability. In other words, subjects would aim for the center of a target and only hit it at a certain probability given their motor variability and bias. The results from Trommershäuser, Maloney, and Landy (Trommershäuser et al., "Statistical Decision Theory and Tradeoffs in Motor Response," 2003; Trommershäuser et al., "Statistical Decision Theory and Rapid, Goal-Directed Movements," 2003) show that the probability of hitting a certain region during a pointing task is a function of motor uncertainty that is normally distributed, with a bias. The deviation from the line connecting the center of the target to the center of the starting position over the duration of 5 ms before and 5 ms after target hit was used to calculate the bias (average error) and standard deviation for each subject. Target radius was calculated by

$$R_p = 0.5 + L_{bias} + z_p\sigma, \quad (1)$$

where R_p is the radius of a given hit probability, L_{bias} is the average error from the line from the starting position to the center of the target, z_p is the z-score for a given probability, and σ is the standard deviation of the deviation from the line from the starting position to the center of the target. A minimum target size was desired, so 0.5 cm was added because that is the same size as the cursor radius. A MATLAB code analyzed the training block data to produce the three target sizes for each subject.

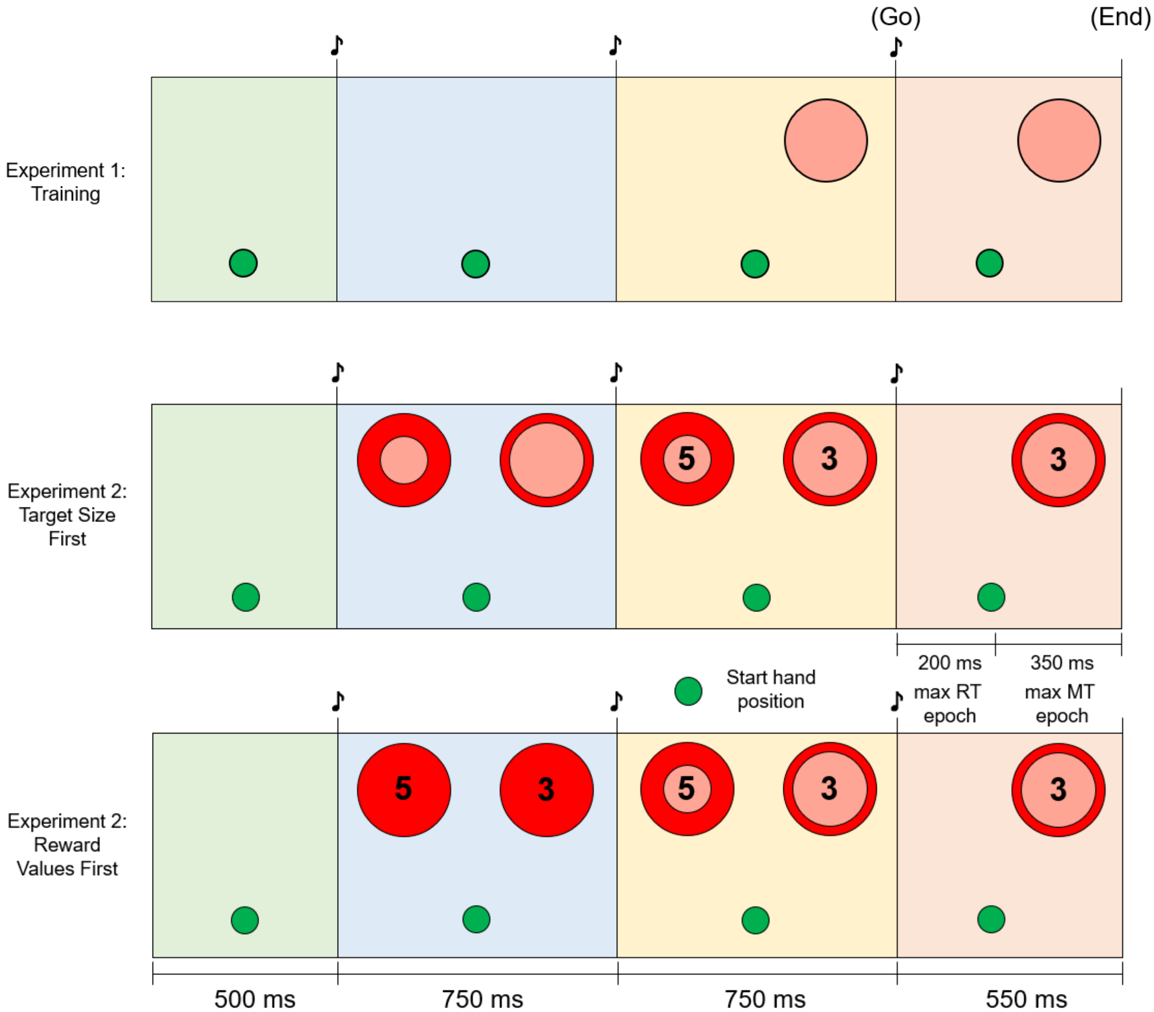

Fig. 1 Experimental Design. Participants initiated movements synchronously with the last of three tones spaced 750 ms apart. Subjects held the cursor in the starting position for 500 ms to begin the trial. Subjects had 200 ms to initiate movement after the third tone and 350 ms to reach through the target after movement was initiated. For Experiment 1 (row 1), there was no outer

target or reward values. Experiment 2 shows an example of a Forced trial, where one target was removed on the third tone. In row 2, the target size was presented on the first beep and the reward values were presented on the second beep. In row 3, reward values were presented on the first beep and target sizes were presented on the second beep. Sizing is not to scale.

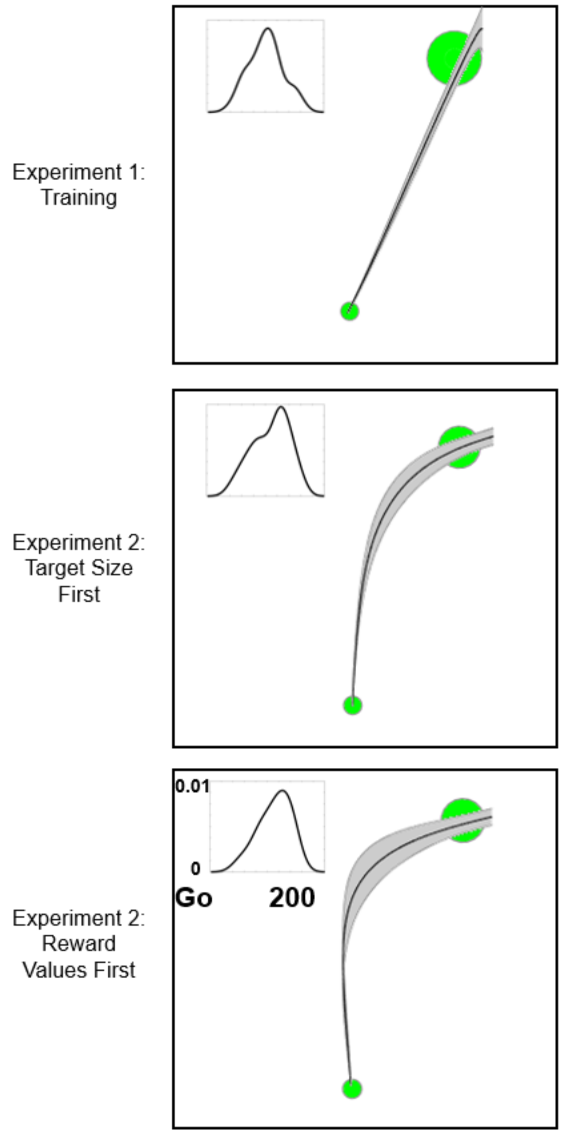

Fig. 2 Average Trajectory for Example Subject. Average trajectories ±1 SD for an example subject for the conditions in Fig. 1. Sizing is to scale. Distributions of reaction times for the given condition are plotted in the top left corner of each trajectory plot.

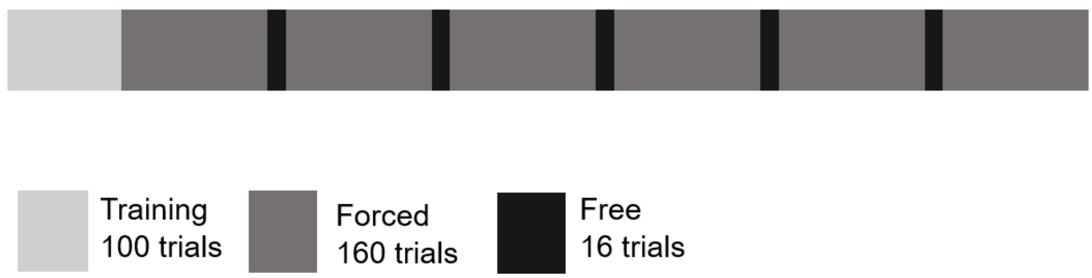

Fig. 3 Block layout of the entire data recording session. A total of 1140 trials were performed in approximately an hour and a half (0.2 hours for Experiment 1, 1.3 hours for Experiment 2).

Changes from Pilot

Several parameters were adjusted after running the Pilot study. During the training session, there were originally three different target sizes (radius = 1.5, 3, and 4.5 cm). The largest target size was removed, and the number of trials increased from 20 to 25 per condition (100 total). The target appeared on the third beep instead of the second beep during the Pilot study. This was changed so there would be no bias from the previous trial in predicting where the target will appear. The inner target radii in the Pilot study were fixed at either 1, 2, or 4 cm. There were four different possible inner target radius ratios of the left target to the right target: 1:2, 1:4, 2:1, and 4:1. An additional level, the 1:1 (50:50) ratio, was added to Experiment 2 after the Pilot study. During the Pilot study, all participants from Experiment 2 participated in Experiment 3 immediately after the completion of Experiment 2 in the same experimental session. The protocol of Experiment 3 was fundamentally the same as the Training block, except the target appeared at a random time (between 375 and 0 ms) before the third tone was played. Movement had still to be initiated on the third tone. Experiment 3 was eliminated to increase the number of trials in Experiment 2. The number of trials in Experiment 2 increased from 800 to 1040 from the Pilot study to the full experiment. Free choice trials decreased from 20% in the Pilot study to less than 8% in the full experiment.

Data Processing

Position and velocity data were smoothed using a third order, double-pass filter with a 3dB cutoff at 10 Hz. Subject inertia and torque values were added with MATLAB programs provided by BKIN Technologies. Time of movement was determined by the pre-programmed event code that corresponded to the center of the cursor moving outside of the starting position. The time of a successful hit of the target was determined by the event code that corresponded to the center of the cursor first entering the target. The analyses focused on three main variables: *Initial reach angle*, *reaction time,* and *curvature*. Initial reach angle was computed as the direction of the cursor after 25 ms in relation to straight ahead from the starting position. Angles clockwise and counterclockwise from straight ahead were defined as positive and negative, respectively. Initial reach angles were then divided by 1 or -1 depending upon the side of the target that remains after the third beep. Reaches towards the correct target are positive and reaches towards the incorrect target are negative. Reaction time was calculated as the time between the third beep event code and the time of movement. Curvature was calculated by:

$$\kappa = \frac{|x'y''-y'x''|}{(x'^2+y'^2)^{\frac{3}{2}}}, \qquad (2)$$

where *x'* and *y'* are the first derivatives of in the x and y direction, respectfully, and *x''* and *y''* are the second derivatives in the x and y direction, respectfully. Curvature analysis was performed on interpolated traces (99 steps). For successful trials, the traces ended once the target was hit. For unsuccessful trials, the first 300 ms of movement were used. The maximum curvature was found for each trace between points 10 and 75. If the curvature was greater than 250, the sign of the trajectory at point 5 was compared to the sign of the trajectory at the end. If the signs were the same (did not cross the midline), then the maximum curvature value from point 10 to 40 of the trace was found. If the signs were different, the original value of the curvature was kept. This was done to avoid any curvature that was not indicative of the change in motor plan. This algorithm was determined from visual inspection. Trials where a movement was not initiated in the 200 ms after the third beep (about 10% of trials) were excluded from data analysis. One participant was excluded from data analysis due to poor performance ('Too Slow' on over 40% of trials).

Data Analysis

Only Forced Choice trials were analyzed. Using Hartigan's Dip Test of unimodality, a probability was calculated for each distribution of initial angle for each subject and reward-target size combination. This probability was the likelihood that the distribution was unimodal. High probabilities corresponded to unimodality, or a Gaussian-like curve, while small probabilities corresponded to bimodality. It was found that there were bimodal distributions when intermediate movements were not present (Wong and Haith, 2017). The behavior linked to the bimodal initial reach angle distributions was reaches straight towards one target regardless if it was the one the subject was supposed to hit. For this experiment, a unimodal initial reach distribution also corresponds to intermediate movements. A mixed model was used to analyze the effects of order, target size, and reward value on the probability of the initial angle distribution being unimodal. Subjects were included as a random effect in the model. The probabilities from Hartigan's Dip Test were calculated in MATLAB and the mixed model was fit in JMP. For reaction time, a full linear fixed effects model was fit first. The full model included the factorial combination of order, reward, and target size as fixed effects. Order was entered as a categorical variable, whereas reward and target size were entered as continuous predictors. The only random effect in the model were the subject intercepts. The full model was fit submitted to subsequent model reduction using likelihood reduction tests. This procedure was done until significant combinations of predictors were left in the model. Analysis was done LME4 package in R. A mixed model was used to analyze the effects of order, target size, and reward value on the curvature. Subjects were included as a random effect in the model. Curvature was normalized by the maximum curvature value from each subject during each condition. This was done after statistical outliers were removed (> ±3 SD, approximately 5% of trials). Significance level was set at $\alpha = 0.05$.

Hypothesized Results

Initial reach angle and reaction times were analyzed to identify the processes and the processing time, respectively, of the motor decision. Curvature was analyzed to identify the changing of motor plans. It was hypothesized a different effect of reward and target sizes on initial reach angle, reaction time, and curvature.

For initial reach angle (Fig. 4), when the reward difference is 2, it was hypothesized that subjects would reach with intermediate movements more than when the reward difference is 5. When the reward difference is 5, a bimodal distribution of initial reach angles would be present because the subject would reach towards the larger reward on each trial, but the target with the larger reward disappears on half of the trials. This would mean that there would be one peak of the bimodal distribution would be a reach towards the correct target and the other peak would be the reach towards the incorrect target. When reward difference is small, the distribution was hypothesized to be unimodal centered close to zero. This is because the difference in reward is not enough to warrant the risk of being wrong, so an intermediate reach is used to wait to accumulate more evidence. It was further hypothesized that when target size is increased for one of the targets, there would be no effect on the initial reach angle distribution. This is because people prioritize reward and are not penalized for missing in this task, so there would be less motivation to reach for the easier target.

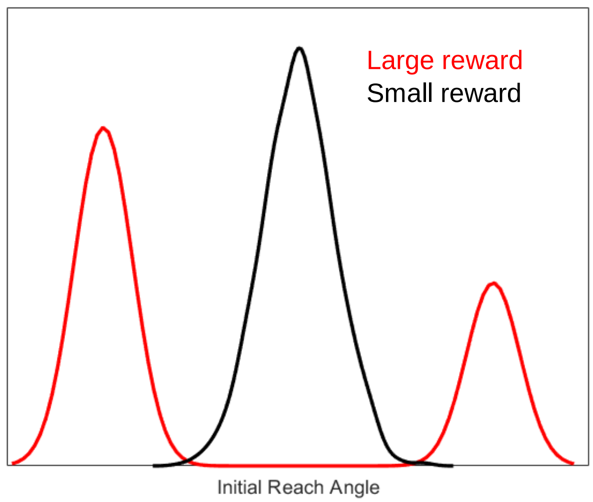

Fig. 4 Hypothesized initial reach angle distributions for Forced trials. Distributions were hypothesized to be unimodal when the reward difference was small and bimodal when reward difference was large.

For reaction time (Fig. 5), it was hypothesized that when the reward difference is increased, subjects will initiate movement earlier. This outcome would imply that reward influences the rate in which motor actions are selected. It was also hypothesized that there would also be lower reaction times when the target size increases. This would indicate that motor costs are also considered when making the decision. It was further hypothesized that reward would have a larger impact on reaction time than target size because people are seeking to maximize reward. Subjects do not know which target is going to remain visible after the third tone, so they would try to obtain the larger reward.

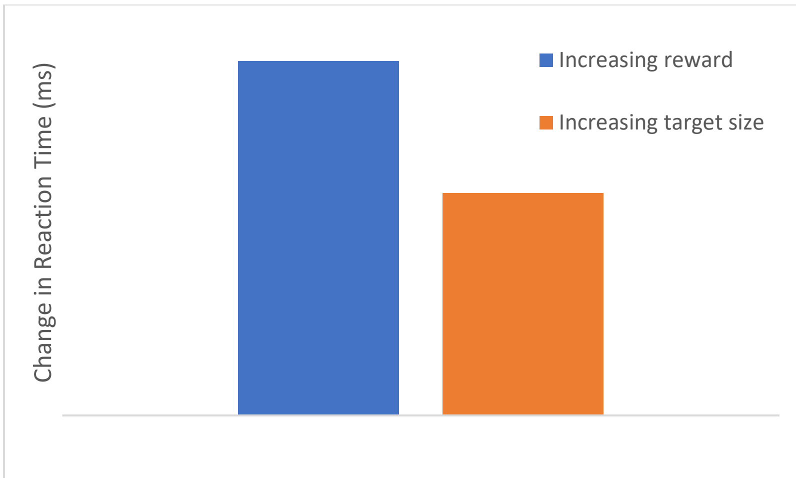

Fig. 5 Hypothesized reaction time for changes in reward and target size.

For curvature (Fig. 6), it was hypothesized subjects would have more curvature when the reward difference between the two targets increases than when target size increases. There would be a more drastic change of plans when the initial decision is wrong. This predicted result relies heavily on the predicted result for the initial reach angle. It was hypothesized that initial decision will be influenced mostly by the reward and that intermediate movements will be used when the reward difference is small. During intermediate movements, less curvature is required to hit a target. For reaches initially towards either of the targets, more curvature would be required when the initial decision is wrong.

Fig. 6 Hypothesized curvature for Forced trials.

RESULTS

Initial Reach Angle

Initial reach angle unimodal distribution probabilities were analyzed by a mixed model to determine the effects of order, target size, and reward value. These results show which factors are strong predictors for changing the presence of intermediate movements. The only significant predictors were reward ($p < 0.05$) and subject ($p < 0.05$). Changing the reward had a negative slope (-0.032). This means that changing the reward difference between the targets with all else constant will decrease the probability of a unimodal distribution, indicating that intermediate movements are less likely. This can be also thought of as a measure for the willingness to select a riskier plan than creating the safer intermediate movement. It makes sense that when the difference in reward between the targets increases, people are more willing to accept the risk of being wrong for the higher reward. Since subjects were analyzed as a random effect, this result can be interpreted as the probability of a unimodal distribution, or intermediate movements, is dependent upon the person. The initial reach angle distributions for an example subject during a given condition can be seen below in Fig. 7.

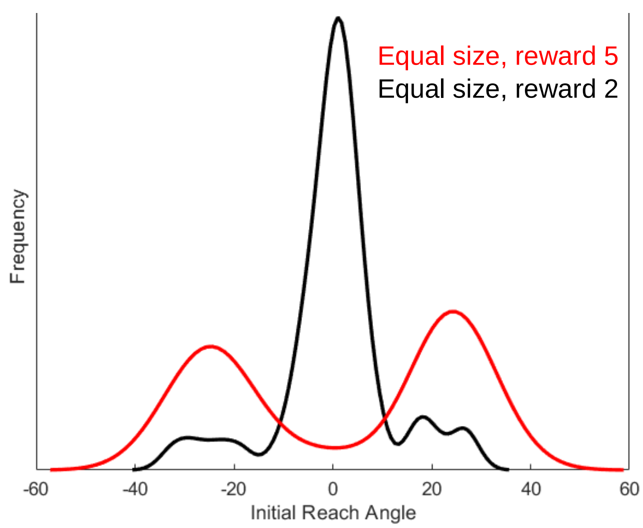

Fig. 7 Initial reach distributions for an example subject. This result was from the equal target size, reward difference of 2 (black) and equal target size, reward difference of 5 (red) conditions during Forced Choice trials.

Reaction Time

Results from the linear fixed effects models show how the reaction time changes when changing factors with respect to the intercept. For reaction time, the significant combinations of predictors included order ($p < 0.05$), reward ($p < 0.05$), target size ($p < 0.05$), and a reward-target size interaction ($p < 0.05$). None of the other interactions were significant. It was found that reaction time was lower when the target sizes were presented first (Fig. 8). Changing the order from reward first to target size first had a negative slope (-2.9). This means that changing the order of information with all else constant will decrease the reaction time by 2.9 ms. This could be a result of the length of time the cue is on the screen and may not necessarily indicate an effect of the order of information presented. Increasing the reward difference had a negative slope (-2.2). This means that changing just the reward difference between the targets by one unit decreases the reaction time by 2.2 ms. This result suggests that the decision is made faster when there is more reward. Increasing the target size difference had a negative slope (-2.0). This means that changing just the target size ratio by one unit decreases the reaction time by 2.0 ms. It is implied by this result when one of the targets become larger and thus has a lower motor cost, decisions are made faster.

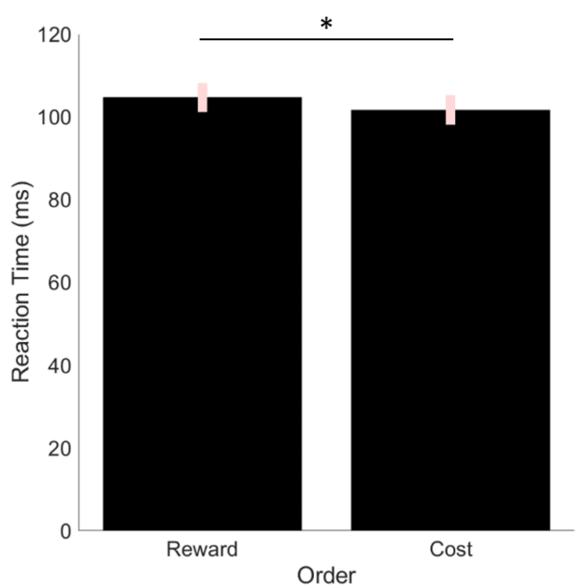

Fig. 8 Average reaction time for the different orders. Error bars represent the S.E.M.

The interaction effect of reward and target size was another important result. As both the reward and target size increased, the slope, or change in reaction time, was more positive (0.46). The change in reaction time is contingent upon the level of reward and target sizes. This result suggests that the expected value difference is considered when making a decision. People were not just responsive to changes in reward and target size, but the combination of their differences. Another mixed model was fit, this time analyzing the effects of expected value difference (ΔEV) on reaction time. Expected value was calculated as the target reward value multiplied by the hit probability. The difference in expected value was calculated as the unintended target's expected value subtracted from the intended target's expected value. A high order polynomial fixed effects model was fit with subsequent model reduction. The significant predictors of reaction time were order (p-value < 0.05), an order-ΔEV interaction (p-value < 0.05), ΔEV^2, (p-value < 0.05), and ΔEV^4 (p-value < 0.05). Changing the order from reward first to target size first had a negative slope (-1.3494). The ΔEV^2 predictor was found to have a negative slope (-0.463). Although small, ΔEV^4 was found to have a positive slope (0.016). Subject (p-value < 0.05) was also a significant predictor of reaction time. It is interesting that ΔEV was not a strong predictor of the reaction time, but higher order, even polynomials were. This result implies that while expected value is considered while making a decision, it is not a linear relationship.

Curvature

Curvature was analyzed across the different reward and size combinations for both order conditions. To account for the right-skewed distribution, a log10 transformation was made on the normalized curvature. For curvature, order ($p < 0.05$), target size ($p < 0.05$), target size-reward interaction ($p < 0.05$), and reward-order interaction ($p < 0.05$) all were significant predictors of curvature (Figs 9 and 10). There was a small effect of changing the order on the normalized curvature (slope = 0.016). Changing the target size had the largest change in the slope of curvature (slope = -0.0958). A likely interpretation of this result is that as the targets become larger and easier to hit, less severe changes in motor plans are required to hit the target, thus curvature is the largest when the target sizes are the smallest. Of the two interactions, the target size-reward interaction had the largest change in the slope (0.0133). Much like the reaction time, this could indicate that expected value could help drive the changing of motor plans. Subjects was also included as a random effect and was significant ($p < 0.05$). In this experiment, curvature is the measurement of the ability to change plans. More curvature can be interpreted as a quicker change in motor output. It could also imply the risk taken by the subject because intermediate movements have less curvature than movements that are initially directed at one target and require a longer path to reach the other target. Since subject was a significant predictor of the curvature, this implies that some people are more willing to take the risk of being wrong with a possibility that they won't have to correct at all.

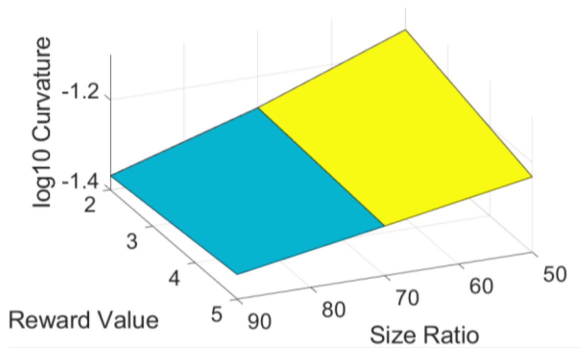

Fig. 9 Curvature for different reward and size combinations, reward shown first.

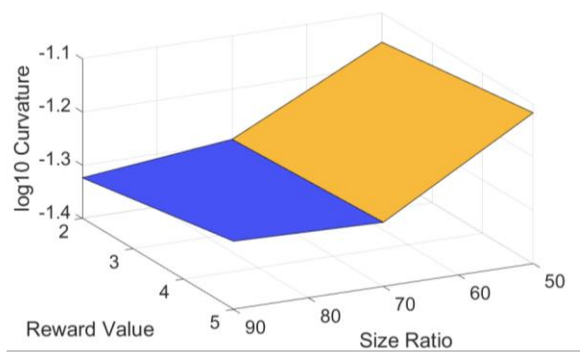

Fig. 10 Curvature for different reward and size combinations, target size shown first.

DISCUSSION

A novel reward-based sensorimotor decision-making task with a go-before-you-know paradigm was developed to assess how reward and motor costs interact to influence decisions. It was found that reward was the only significant factor for increasing the probability of performing riskier movements instead of the safer alternative of intermediate movements, which confirms the initial hypothesis. The effect of subjects also influenced the initial reach, which supports the idea that some people are more willing to risk missing the target in favor of a higher reward. It is interesting to note that target size did not influence the initial reach. One possible result could have been that people would always reach towards the larger target, but this was not the case. A possible explanation for this finding is that since there was no penalty for missing, there was less motivation to aim for the easier and safer option. If there was a penalty for missing, it can be hypothesized that the target size would also influence the initial reach.

Not only did both reward and target size have an effect on the reaction time, but the interaction between the two also had an effect. This supports the idea that expected value drives the decision-making process. Changes in both reward and target size were processed at a different rate than changing both factors separately, which suggests that the plan is driven by the expected value of the targets. The results from the polynomial fixed effects model indicated that higher order, even polynomials are strong predictors for reaction time. While one explanation could be that the expected value difference has a nonlinear relationship, a more plausible explanation is that the model included negative expected value differences and people don't process this. The latter explanation is supported by the fact that participants did not know which target would remain after the third beep, so there is no way to process an expected value difference with respect to the intended target.

One approach to modeling decision-making is by expected value, where the cost of the decision, in this case motor difficulty, is considered along with the reward (Loewentein and Prelec, 1992; Bach et al., 2017; Daw and Tobler, 2013; Rolls et al., 2008). Another approach to describe how decisions are made is divisive normalization (Zimmermann et al., 2018; Louie et al., 2015). Both methods try to account for the value of decision and the relative motor costs of making each decision. Various other probabilistic models have been created to describe the decision-making process (Watson, 2017; Burk et al., 2014). The reaction time results suggest that expected value drives the decision-making process and is the best model. The motor costs here were represented by the theoretical hit probability given the subject's motor variability. It is entirely possible that motor costs are processed and integrated in some other relationship, but the data suggests that the expected value of the target plays a role in the decision-making process.

Once an initial decision was made, the changing of motor plans, measured by curvature in this experiment, was modulated by the motor costs required to change plans and hit the intended target. There also was a target size-reward interaction effect. One interpretation of this result is that the curvature required to change plans and hit the remaining target is driven by the expected value of the remaining target. If the intended target has a high enough expected value, there might be more motivation to change plans and attempt to hit the target. An example of this is for an intermediate movement between the 90% hit probability target with a reward value of 3 and the 50% hit probability target with a reward value of 5. If the target with a 50% hit probability worth 5 points disappears, there is still enough value in the intended target to warrant a reach. Conversely, there may not be enough value in switching plans to aim for the target with a 50% hit probability and a reward of 1 after creating an initial movement towards a target with 90% hit probability and a reward of 6. This could indicate conditional decision-making driven by the expected value difference between the targets. However, this data is unable to fully address this question.

There was an effect of the framing on the reaction time and curvature results. One possible explanation for this is that the time that the information was displayed affected the evidence accumulation and attention. What was shown first could have had more weight on the evidence accumulation than what was shown second. This potential confound was identified and controlled for in the experiment to acknowledge a possible difference in the framing of the information presentation. While there were statistically significant differences related to the framing, this is not a result of interest because it was a control in the study.

CONCLUSION

There is evidence that reward and motor costs interact during the decision-making process. Both reward and motor costs influence the motor planning and selection of a decision, but their interaction was also shown to have an effect. This supports the idea that expected value also drives the planning of the decision. Subjects were initially drawn towards a larger reward, but the motor costs influenced the change in motor plans. This suggests that there was planning for both the initial reach and the adjustment required in case the initial decision was incorrect.

More work needs to be done with different paradigms to determine how expected value can influence decisions, which provides insight on the modulation of motor controller gain. Different ways to manipulate motor costs, like a force-field perturbation, would give further insight on how motor control gain is modulated during decision-making. The interaction between reward and motor costs might change the decision-making process with the different ways that motor costs can be manipulated. Reward could also be changed as well, perhaps will awarding more points for reaches that are closer to the center of the target. Implementing these changes in reward and motor costs are good candidates for designing future studies to investigate this field of research. This would provide further depth on how reward and motor costs are integrated into decisions, expanding the knowledge of this particular type of value-based decisions between competing options.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL

IRB identification number STUDY00006050 has been approved by Arizona State University.

APPENDIX B

CONSENT FORM

CONSENT FORM

Neural and behavioral basis of sensorimotor control and learning

INTRODUCTION

The purposes of this form are to provide you (as a prospective research study participant) information that may affect your decision as to whether or not to participate in this research and to record the consent of those who agree to be involved in the study.

RESEARCHERS

Principle Investigator:

Marco Santello, Ph.D., School of Biological and Health Systems Engineering, Fulton College of Engineering

DESCRIPTION OF RESEARCH STUDY

These studies our focused on examining how the brain produces movements of the body, and how the brain manages the coordination of muscles through measurable electrical brain activity. We are examining these questions in people from ages 18-50. You will be tested on a series of tasks to examine your basic motor abilities. If you decide to participate in the experiment, you may be asked to participate in a version involving either transcranial magnetic stimulation (TMS), transcranial focused ultrasound (TFUS), somatosensory evoked potential (SEP), and/ or electroencephology (EEG). In the case that these methods will be employed, you may be asked to also obtain an MRI of your brain. This will be done off campus and will require one of the researchers to bring you to the MRI facility. The MRI costs will be covered by the researchers. The combination of these methods will allow us to accurately track how the spatial and temporal dynamics of your brain activity changes during the course of an experiment. For any of the below experimental protocols, there is only one session. However, you may be invited to come back and participate in other experiments as sessions separate from the original. Therefore, any compensation for participation is for each individual session.

In some instances, you will be asked to lift objects up from the table, hold them, and replace them. The task and objects may include those encountered in activities of daily living (coffee mug, water bottle, etc), or instrumented object equipped with force sensors (ATI). We may also change object properties such as mass (usually less than 1000 g and up to 2000 g if two hands are used), center of mass, or texture of the graspable surfaces. Reflective markers will be attached to the object and/or hand using a tape to track the motion of the object and/or the hand while subjects perform various tasks. You will you're your right hand and/or left hand and grasp the object with 2, 3, or 5 digits. During lifting, you may be required to control the orientation of the objects, hold it for less than 5 seconds, and replace it on the table. Each experimental session consists of several blocks of trials. In some versions of this task, you will be asked to perform object lifting and manipulation together with another person. The total number of trials during one session would not exceed 250 (usually less than 40). During some portions of the task, you will either receive TMS or ultrasound, while in most cases we will record EEG from your scalp. If using any of these recording or stimulation modalities, we will also record electromyographic activity from the surface of your muscles. In addition, to reveal sensorimotor integration including somatosensory pathways during a motor task, SEP will be recorded using combined EEG and electrical peripheral nerve stimulation. SEP is the widely used method in neuroscience research field. Peripheral nerve stimulation poses no risks to the participant, is painless, and is the most widely used non-ivasive method to assess sensory system.

In some instances, you will interact with a virtual reality (VR) environment by applying forces with their thumb and index finger to levers attached to robotic devices. The robotic devices are motorized mechanical linkages that generate forces in response to forces exerted by the fingertips, thus generating the feeling of grasping a real object. To strengthen this feeling, the perceived object is displayed on a computer monitor placed in front of the subject. The maximum output of the device is limited to very small forces (up to a maximum of 6 Newtons). The VR environment contains virtual objects that participants need to grasp and manipulate through the robotic device. When not performing the task, participants can rest their hand and forearm on a foam pad. Each experimental session consists of several blocks of trials. The total number of trials during one session would not exceed 300 (usually less than 150). Participants may need to come back for subsequent sessions with the same or similar task requirements. The inter-session time varies between hours and days.We will collect EEG data during task performance, while simultaneously applying either TMS, TFUS or electrical peripheral nerve stimulation.

In other instances, you will be asked to move a cursor on a screen using a mouse or a force transducer. The task requires you to respond as quick as possible to visual stimuli presented on a screen in front of you. The visual stimuli will consist of geometric shapes such as circles or triangles, or alphabetic characters from different languages. Each experimental session should not involve more than 600 trials. These sessions will also involve the collection of EEG data during task performance, while simultaneously applying either TMS or TFU.

When performing one of the above tasks, we may ask you to return to participate in other versions of the task to allow us comparison of your learning performance across several types of tasks.

If you say YES, then your participation in the study will last approximately two hours for any given session, at PEBE 174. Approximately 1200 people will be participating in the study.

RISKS

The current methods carry minimal safety risks. Some people report that their scalp muscles have discomfort, and/or a headache comes and goes after TMS, though both of these issues are less of a problem in the particular scalp areas we will be stimulating. Headaches from TMS can occur. Though, they are very uncommon, and most participants report these headaches as minor and being a 1-2 on a scale of 1-10 (10 being most severe). These headaches can last approximately 1 to 2 hours at most. Headaches have not been reported anywhere to last longer than this duration. TMS involves discharging brief magnetic pulses over the head. Possible ·effects on hearing have been described and so subjects and investigators will be asked to wear earplugs during any TMS to avoid this possibility. While no current evidence is available which suggests TMS may be damaging to fetus, pregnant females will not be included in the study. As with any electronic device or appliance, using it the wrong way could result in electric shock. While this is very, very unlikely, it cannot be completely excluded as a possibility. The risks of injury or discomfort in this research are minimal.

Recording of EEG is the most widely used method of neural data recording. It involves placing sensors in a cap, that is worn on the head. Because it is a passive recording system of electrical brain activity, it has no known or foreseeable risks.

The application of TFUS involves placing an ultrasonic transducer upon the head and discharging brief ultrasonic pulses. This process may produce a vibration/buzzing sensation upon the scalp and may also result in a warming sensation. If you feel discomfort at anytime during this application, please inform the research team and stimulation will be halted.

AS for recording of SEP, a bar electrode is attached at the skin of your wrist. Weak electrical current will deliver over the skin of your limb at 1-5 Hz. Basically, SEP recording is considered very safe and no-risk procedures. However, sometimes you may feel minor discomfort in the form of momentary peripheral tingling due to electrical stimulation. If you feel discomfort at anytime during this application, please inform the research team and stimulation will be halted.

There is a possibility that the linkage system will move you at an uncomfortable speed, however, several safety precautions have been implemented to reduce this risk. Specifically, the maximal speed of the movement imposed by the linkage system is set below human physiological limits. If these speeds are exceeded the linkage system is designed to immediately shutdown. Although your fingers you will be attached to the device via Velcro-like straps, you will be able to remove your fingers from the device if you feel any discomfort to let go of the object to protect yourself from potential discomfort, pain, or injury. The metal cylindrical object is powered and connected to the USB port of a pc with proper shielding and grounding. The risk of getting static shock is no different than using metal objects in daily life. However, as with any research, there is some possibility that you may be subject to risks that have not yet been identified.

BENEFITS

Although you will not benefit individually from participation in the research, this study will help us to understand the relationship between the brain's capacity to change and sensorimotor learning. This information will be used to guide further studies in brain injured populations.

NEW INFORMATION

If the researchers find new information during the study that would reasonably change your decision about participating, then they will provide this information to you.

CONFIDENTIALITY

All information obtained in this study is strictly confidential unless disclosure is required by law. The results of this research study may be used in reports, presentations, and publications, but the researchers will not identify you. In order to maintain confidentiality of your records, Marco Santello or Justin Fine will code all of your information so your identity cannot be determined from any of the data. The key to the code is kept in a separate location from the data and the data are locked in a cabinet. Only Marco Santello or Justin Fine and the research assistant that enrolled you in the study will have access to both the codes and the code key.

WITHDRAWAL PRIVILEGE

It is ok for you to say no. Even if you say yes now, you are free to say no later, and withdraw from the study at any time. Your decision will not affect your relationship with Arizona State University or otherwise cause a loss of benefits to which you might otherwise be entitled.

COSTS AND PAYMENTS

The researchers want your decision about participating in the study to be absolutely voluntary. Yet they recognize that your participation may pose some inconvenience. You will be paid $20 for each session. All payments are made at the end of each phase.

COMPENSATION FOR ILLNESS AND INJURY

If you agree to participate in the study, then your consent does not waive any of your legal rights. However, no funds have been set aside to compensate you in the event of injury.

VOLUNTARY CONSENT

Any questions you have concerning the research study or your participation in the study, before or after your consent, will be answered by one of the following people: Dr. Marco Santello (480-965-8279), Justin Fine (480-965-8279), or Qiushi Fu (480-965-8279).

If you have questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk; you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at 480-965 6788.

This form explains the nature, demands, benefits and any risk of the project. By signing this form you agree knowingly to assume any risks involved. Remember, your participation is voluntary. You may choose not to participate or to withdraw your consent and discontinue participation at any time without penalty or loss of benefit. In signing this consent form, you are not waiving any legal claims, rights, or remedies. A copy of this consent form will be given (offered) to you.

Your signature below indicates that you consent to participate in the above study.

_____________________________ _____________________________ ____________

Subject's Signature Printed Name Date

INVESTIGATOR'S STATEMENT

"I certify that I have explained to the above individual the nature and purpose, the potential benefits and possible risks associated with participation in this research study, have answered any questions that have been raised, and have witnessed the above signature. These elements of Informed Consent conform to the Assurance given by Arizona State University to the Office for Human Research Protections to protect the rights of human subjects. I have provided (offered) the subject/participant a copy of this signed consent document."

Signature of Investigator_________________ Date_________

APPENDIX C

TARGET SIZE DETERMINATION CODE

```
subjects = [26]; %Change number based on analyzing everyone or just
doing 1 subject
for i=1:length(subjects)
    s=subjects(i);
    load(strcat('TRAIN_Subject_',num2str(s),'.mat')) %Pilot

    for i=1:length(KinData)

        try
            dat=[100*(KinData(i).Right_HandX(1:end)-
KinData(i).Right_HandX(1)),100*(KinData(i).Right_HandY(1:end)-
KinData(i).Right_HandY(1))];

            da=dat(KinData(i).HITTIME,:);
            data=mean(da,1);
            if sign(KinData(i).Right_HandX(KinData(i).HITTIME))==1
                x2=5.740;%/100;
                y2=13.8580;%/100;
            elseif sign(KinData(i).Right_HandX(KinData(i).HITTIME))==-1
                x2=-5.740;%/100;
                y2=13.8580;%/100;
            else

            end
            distend(i)=(sign((x2-abs(data(1,1))))*sqrt(((x2-
abs(data(1,1))).^2)));%KinData(i).targetAsize;
%             figure;
%             plot(dat(1,:),dat(2,:))
%             plot(dat(:,1),dat(:,2))
            LastX = 100*(KinData(i).Right_HandX(KinData(i).HITTIME-
5:KinData(i).HITTIME+5)-KinData(i).Right_HandX(1));
            LastY = 100*(KinData(i).Right_HandY(KinData(i).HITTIME-
5:KinData(i).HITTIME+5)-KinData(i).Right_HandY(1));
            DfromLine{s,i}=Deviation_from_line(0,0,x2,y2,LastX,LastY);
            MinDev(i) = mean(abs(DfromLine{s,i}));

        catch
            distend(i)=NaN;
            DfromLine{s,i} = NaN;
            MinDev(i) = NaN;
        end
    end

    distout(s,1)=nanmean(distend);
    distout(s,2)=nanstd(distend);
    DevFromLine(s,1)=nanmean(MinDev);
    DevFromLine(s,2)=nanstd(MinDev);
end

sd1 = norminv(0.5);
sd2 = norminv(0.7);
sd3 = norminv(0.9);

for i=1:length(subjects)
    s=subjects(i);
```

```
    Devtarget1size(s) =
0.5+abs(DevFromLine(s,1))+sd1*(DevFromLine(s,2));
    Devtarget2size(s) =
0.5+abs(DevFromLine(s,1))+sd2*(DevFromLine(s,2));
    Devtarget3size(s) =
0.5+abs(DevFromLine(s,1))+sd3*(DevFromLine(s,2));
end

% for i=1:length(subjects)
%     s=subjects(i);
%     target1size(s) = abs(distout(s,1))+sd1*(distout(s,2));
%     target2size(s) = abs(distout(s,1))+sd2*(distout(s,2));
%     target3size(s) = abs(distout(s,1))+sd3*(distout(s,2));
% end

for i=1:length(subjects)
    s=subjects(i);
    fprintf('Largest target for Subject %2.0f should be %2.4f in radius
\n',s,Devtarget3size(s))
    fprintf('Medium target for Subject %2.0f should be %2.4f in radius
\n',s,Devtarget2size(s))
    fprintf('Smallest target for Subject %2.0f should be %2.4f in
radius \n',s,Devtarget1size(s))
end
```