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Abir Hajri, Sidney Fels, Gregor Miller, Michael Ilich

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Abir Al Hajri, Sidney Fels, Gregor Miller, and Michael Ilich

Human Communication Technologies Laboratory, University of British Columbia, Vancouver, BC, Canada
{abira, ssfels, gregor, michaeli}@ece.ubc.ca

Abstract. Target selection is a fundamental aspect of interaction and is particularly challenging when targets are moving. We address this problem by introducing a novel selection technique we call Hold which temporarily pauses the content while selection is in progress to provide a static target. By studying users, we evaluate our method against two others for acquiring moving targets in one and two dimensions with variations in target size and velocity. Results demonstrate that Hold outperforms traditional approaches in 2D for small or fast-moving targets. Additionally, we investigate a new model to describe acquisition of 2D moving targets based on Fitts' Law. We validate our novel 2D model for moving target selection empirically. This model has application in the development of acquisition techniques for moving targets in 2D encountered in domains such as hyperlinked video and video games.

Keywords: Human performance modeling, Fitts' Law, 1D Selection, 2D Selection, Moving target selection

1 Introduction

Selection is one of the fundamental and most commonly occurring tasks of interaction between humans and computers for applications such as games, surveillance, simulations, web browsing, and rich media. Understanding the effects of target factors in selection and how those factors interact with human cognitive, perceptual and motor control systems helps to optimize user performance and interaction design. Some of these factors have been studied and analyzed extensively for stationary targets while moving targets lacks similar consideration. Target acquisition becomes a critical task when trying to select moving targets at different speeds and sizes such as occurs in hyperlinked video where active objects in the video are moving. This type of interaction is emerging as video becomes ubiquitous media on the web for example. Previous research has investigated methods to ease the selection task by introducing various effective selection techniques [24, 16, 18].

The research presented in this paper makes two contributions to the interaction literature. First, we derive and validate a new model for target acquisition which extends Fitts' Law to accommodate moving targets in both one and two dimensions. The model we present calculates the index of difficulty and movement time for moving targets by incorporating target speed, relative direction and movement angle. Second, we present and demonstrate the effectiveness of a novel target acquisition method we call Hold (also referred to as Click-to-Pause) which improves upon existing selection techniques for moving targets.

Our motivation comes from live action sports footage where both the objects of interest (players, adverts, etc.) and the camera can move, creating a difficult scenario for object selection. However the problem of moving target acquisition applies generally to video games, rich media, web-site design and other dynamic interaction-based media. Selecting a moving target is a challenging interaction task, especially compared with that of selecting static targets. A moving target in one dimension is either moving toward or away from the cursor: in the former a rendezvous is required to acquire the target, with different directions of motion for observer and target, and a possible reversal of observer motion if the target passes by the observer. The difficulty of the task increases if either the target size is decreased or the target speed is increased. The complexity of the problem is increased when attempting target selection in two dimensions due to variations in target velocity, non-intersecting paths of observer and target motion and the predictability of target motion. Thus, we have created our Hold technique to mitigate this challenge by helping the user select objects while watching the video without the need to use a separate pause button every time they need to do so or chase a moving target which can be very difficult. Hence, watching video while selecting moving hyperlinks does not feel like a video game

We will initially review previous research including Fitts' Law and its subsequent extensions as well as various techniques proposed for target selection. We then describe our extension to Fitts' Law which models moving targets in 2D and introduce our solution to moving target acquisition, Hold. Following this we outline our experiment which validates the model and evaluates Hold against a traditional approach, then we discuss the results of the experiment and how the selection techniques fit within our model. Finally, we conclude the paper by reflecting on the impact of the experiment and providing direction for future research.

2 Review of Previous Work

Rapid aimed movements can be characterized using two different motor control models: the iterative corrections model (Fitts' model [11]) or the impulse variability model (Schmidt et al. model [26]), which depends totally on the task demands. Wright and Meyer [31] have indicated that the iterative corrections model is applied to tasks with spatially constrained movements while the impulse variability model applied to tasks with temporally constrained movements. Spatially constrained movement tasks are those where movements end within a target region while trying to minimize the average movement time. Temporally constrained movement tasks are those where movements are initiated having specified durations in mind while the movements end nearby a target point, not a region. Since our approach involves spatially constrained movements, we characterized and derived our model by extending Fitts' law.

Fitts' Law [11] is the most commonly used approach to study new acquisition techniques, since it was the first successful model to predict the time required to complete an acquisition task. The index of difficulty (*ID*) is modeled on a logarithmic scale depending on target width (*W*) and distance from cursor (*D*); movement time (*MT*) is modeled as a linear relation of *ID*:

$$ID = \log_2\left(\frac{D}{W} + 1\right) \quad (1)$$

$$MT = a + b \times ID \quad (2)$$

where *a, b* are empirically determined constants. This equation was initially proposed for stationary targets in 1D which also assumed that the direction of movement is collinear with *W*. However, it is not an applicable time predictor for 2D pointing tasks.

To modify Fitts' Law to account for 2D targets, several factors should be taken into consideration beyond the target width and distance constraints of the 1D Fitts' Law. 2D pointing is constrained by the target area, the location of the target from the cursor (i.e. the 2D vector representing angle and target position in 2D). Bivariate pointing was first studied by MacKenzie and Buxton [21], where they tested five different formulae to model the index of difficulty and found two of them fit with their experimental results. Their first correlated formulation substitutes the magnitude of the target in the direction of movement (*W'*) for *W* and thus:

$$ID_{W'} = \log_2\left(\frac{D}{W'} + 1\right) \quad \textbf{(3)}$$

Their second formula, which is highly correlated to their experimental data, substitutes the smaller value of a target's width (*W*) and height (*H*). The index of difficulty is then:

$$ID_{\min} = \log_2\left(\frac{D}{\min(W, H)} + 1\right) \quad \textbf{(4)}$$

Accot and Zhai [2] later identified problems with these formulations: Equation 3 ignores height (shown to have an effect by Sheikh and Hoffmann [27]), while Equation 4 considers only one dimension and ignores the angle of approach. Accot and Zhai proposed a weighted Euclidean model (Equation 5) which addressed the dimension issue.

$$ID_{WtEuc} = \log_2\left(\sqrt{\left(\frac{D}{W}\right)^2 + \eta\left(\frac{D}{H}\right)^2} + 1\right) \quad \textbf{(5)}$$

Accot and Zhai's model is similar to the Euclidean norm, with the addition of the parameter η, which weights the effect of height differently from the effect of width. However, the Accot and Zhai's formulation does not account for the angle of the target from the cursor and is constrained to rectangular targets. Therefore, Grossman and Balakrishnan [14] proposed a probabilistic model that is generalized to any target shape, size, orientation, location and dimension.

For moving targets, Jagacinski et al. [19] and Hoffmann [17] investigated how moving targets at constant speed affected the index of difficulty in Fitts' Law. Jagacinski et al. [19] used empirical data from their study to derive an estimate of the index of difficulty for pursuing a moving target in 1D. Hoffmann [17] gave three different extensions to the Fitts' Law: using a first order continuous control system, a second order continuous control system, and a discrete response model. For our 2D moving target selection models, we are going to extend his first order continuous control system model ID_{1st}:

$$ID_{1st} = \ln\left(\frac{D \pm \frac{V}{K}}{\frac{W}{2} - \frac{V}{K}}\right) \tag{6}$$

where K is an empirically determined constant. We also derive this same model using Card's [8] formulation. This is one of the models we empirically investigate to determine how well it fits actual human performance.

Researchers have also proposed interaction techniques to help users select targets by reducing ID as implied by the Fitts' extended models. One approach consists in decreasing the distance from the cursor to the target (D) such as moving targets closer to the cursor [4], skipping empty space between targets by jumping from one target to another [15, 3] or using empty space between targets to increase the effective width and decreasing D [5]. These techniques are affected by the layout of objects on screen and tend to work best when targets are sparse on the screen.

Several other methods also focused on modifying the effective width either by increasing the target width [23, 32], cursor area 10, 16, 20, 30] or effective width (activation area) [13, 5, 9]. Expanding target size or cursor area out-performs the regular technique for the selection of single isolated targets but they do not perform well with clustered or dense areas of targets as selection ambiguity and visual distraction arise. Those techniques also do not address the speed of targets.

There also have been some efforts [6, 10, 29, 30] to improve the target acquisition time by changing the control-display (CD) gain (the ratio between distance moved by the physical input device and distance moved by the visual cursor). By increasing the CD gain in the empty space and decreasing it when the cursor is reaching or over targets, the motor space D/W ratio is decreased. However, they faced problems when distractors are present as these reduce cursor movement time degrading performance compared to regular pointing. Empirical studies have evaluated the effect of similar techniques on selecting moving targets and on acquisition time [16, 24]. However, these techniques faced similar problems with stationary targets as visual distractions and ambiguity in the case of multiple targets. As in real applications such as games (e.g. real-time-strategy games where the selection of moving objects is not the task of the game) and interactive videos, this is an issue which could degrade the performance in selection. In this paper we use our approach to freeze target motion to allow selection without visual distraction. An overview of our methodology is provided in the following sections.

3 Modeling Target Acquisition

Our approach extends Fitts' Law to accommodate moving targets in both 1D and 2D. Fitts' model [11], shown in Equation 1, is valid for stationary objects in 1D. Jagacinski et al. [19] and Hoffmann [17] showed that this model failed to predict accurately the acquisition time for moving targets at a constant speed. They found that including target speed in the index of difficulty of a task showed an excellent fit with the mean acquisition time.

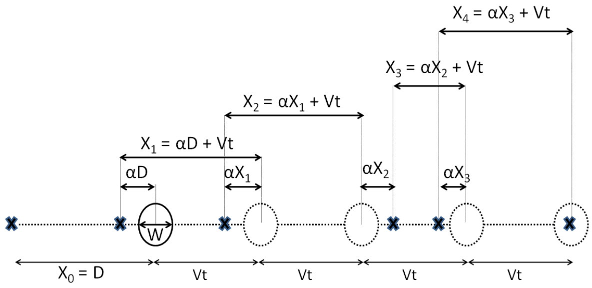

Fig. 1. Analysis of a moving target in 1D

Therefore, the model used to predict the acquisition time of moving targets must include target speed. To accommodate target speed in the model, we applied a model proposed by Card [8] and extended it to moving objects. Each acquisition task involves a ballistic phase and a corrective phase which could be considered as smaller acquisition subtasks. Card used these subtasks to derive a model similar to the approach taken in the steering law for a straight path [1]. The acquisition time is determined by human cognitive, perceptual and motor control systems. Each single movement needs perceptual processing time (τ_P), cognitive processing time (τ_C) and motor processing time (τ_M) to move the hand towards the target. Therefore, n correction movements will need $n\ (\tau_P + \tau_C + \tau_M)$ of time to capture the target [8].

By applying Card's model, we took the remaining distance after each move where the initial remaining distance (X_0) is the initial distance between the cursor and the target D. Let the relative accuracy to reach a target in each move be , then the remaining distance after the first move will be $X_1 = X_0 = D$. We should take into consideration that our target is moving at constant speed V which by the end of the first move after some time t will have already moved Vt. Then X_1 will be $D + Vt$ as the target moves away from the cursor which is illustrated in Fig. 1. Continuing with this argument, we get the following for n moves:

$$\begin{aligned} X_n &= X_{n-1} + Vt \\ &= \alpha^n D + Vt\left(1 + \alpha + \alpha^2 + \ldots + \alpha^{n-2} + \alpha^{n-1}\right) \\ &= \alpha^n D + Vt\left(\frac{1-\alpha^n}{1-\alpha}\right) \end{aligned}$$

using a geometric series. If the target is captured at this point then X_n should be $X_n = W/2$ and if we solve for n:

$$n = -\log_2\left(\frac{D \pm \frac{V}{K}}{\frac{W}{2} - \frac{V}{K}}\right) \Big/ \log_2 \alpha \tag{7}$$

$$MT = n\left(\tau_p + \tau_C + \tau_M\right) \tag{8}$$

$$= \frac{-(\tau_p + \tau_C + \tau_M)}{\log_2 \alpha} \log_2 \left(\frac{D \pm \frac{V}{K}}{\frac{W}{2} - \frac{V}{K}} \right) \quad \textbf{(9)}$$

where $K = (1 - \alpha)/t$, which is empirically determined and the ± indicates the direction of movement i.e. towards or away from the cursor . Then the acquisition time and index of difficulty is:

$$ID_{C_1} = \log_2 \left(\frac{D \pm \frac{V}{K}}{\frac{W}{2} - \frac{V}{K}} \right) \quad \textbf{(10)}$$

This model coincides with Hoffmann's first order continuous-control model [17] for the moving targets in Equation 6.

For our second model of moving target selection in 2D, we look first at how the acquisition time of stationary objects in 2D is modeled and then extend it to moving targets. We adopted Accot and Zhai's weighted Euclidean model (shown in Equation 5) [1]. However, as we mentioned earlier this model does not count for possible differences in performance due to varying movement angles. Therefore, we applied an approach proposed by Grossman and Balakrishnan [12] for pointing targets in 3D. They accommodated angles by adding an additional empirically determined weight parameter $f_{W;H;D}(\theta)$ (width, height and depth) for each component in the weighted Euclidean model. We applied their model by removing the third dimension constraint (depth). Hence our modified weighted Euclidean model becomes:

$$ID_{P_2} = \log_2 \left(\sqrt{f_W(\theta)\left(\frac{D}{W}\right)^2 + f_H(\theta)\left(\frac{D}{H}\right)^2} + 1 \right) \quad \textbf{(11)}$$

For the sake of completeness, this model is compared with $ID_{W'}$ (Equation 3) proposed by MacKenzie and Buxton [21] after extending it to accommodate the possible effects of different target dimensions and various movement angles. From this perspective, the model becomes:

$$ID_{WtW'\theta} = \log_2 \left(f_{W'}(\theta)\left(\frac{D}{W'}\right) + 1 \right) \quad \textbf{(12)}$$

Next, we need to include the target speed to the ID_{P2} model in Equation 11. Therefore, we combined the model we discussed for moving targets in 1D (ID_{C1})and the model for stationary targets in 2D (ID_{P2}). We revised our ID_{C1} model and broke the target velocity V into x and y components as follows:

$$V_x = V\cos(\theta), \qquad V_y = V\sin(\theta)$$

Thus the resulting index of difficulty ID_{C2} incorporating target speed is

$$ID_{C_2} = \log_2\left(\sqrt{f_W(\theta)\left(\frac{D \pm \frac{V_x}{K}}{\frac{W}{2} - \frac{V_x}{K}}\right)^2 + f_H(\theta)\left(\frac{D \pm \frac{V_y}{K}}{\frac{H}{2} - \frac{V_y}{K}}\right)^2} + 1\right) \quad (13)$$

Incorporating target velocity V in a similar manner into the $ID_{WtW'\Theta}$ model results in

$$ID_{VWtW'\theta} = \log_2\left(f_{W'}(\theta)\left(\frac{D \pm \frac{V}{K}}{\frac{W'}{2} - \frac{V}{K}}\right)\right) \quad (14)$$

The $ID_{VWtW'\theta}$ model looks complicated as it is presented in the current formulas; however, by using vector notation, we could rewrite it in a much simpler way and it could even be updated to 3D with an update to the assumptions.

$$\vec{V} = \frac{1}{K}\begin{bmatrix} V_x \\ V_y \end{bmatrix},\ \vec{R} = \frac{1}{2}\begin{bmatrix} W \\ H \end{bmatrix},\ \vec{D} = \begin{bmatrix} D_x \\ D_y \end{bmatrix},\ and\ \vec{F} = \begin{bmatrix} \sqrt{f_W(\theta)} \\ \sqrt{f_H(\theta)} \end{bmatrix}$$

By taking $\vec{V}$ as the velocity vector, $\vec{R}$ as the object vector, $\vec{D}$ as the distance vector between the cursor and the target and $\vec{F}$ as the weighted vector, the extended model will simply be

$$ID_{C_2} = \log_2\left(\left|\vec{F} \cdot \frac{\vec{D} + \vec{V}}{\vec{R} - \vec{V}}\right| + 1\right) \quad (15)$$

From the $ID_{VWtW'\theta}$ model (Equation 14) we can see that the index of difficulty increases as the speed increases or the size decreases while keeping other factors constant. The model also predicts that targets moving towards the cursor (i.e., chasing behaviour) have a larger index of difficulty than those moving away (i.e., pursuit behaviour). To validate these models, we conducted a user study as described later in the paper. We did not use sport videos for our user studies to avoid any uncontrolled factors that could make the validation of the models challenging. Instead we run controlled experiments following Fitts' protocol.

4 Moving Target Selection Technique

We created a selection technique called Hold to overcome some of the drawbacks of previous methods and to reduce the difficulty of moving target selection. Our approach removes speed as a contributing factor to the index of difficulty of selecting moving targets; thus reducing the task to a simple 2D static selection task.

Hold works as follows: when a user clicks the mouse button down, the moving targets temporarily pause while the user interacts with targets. When they release the button, the target starts moving again. The active engage of the motor system allows users to be aware of the temporary nature of the paused state which should reduce confusion [7, 22]. This approach removes the factor of target speed from the task of selecting a moving target on the basis of its distance from a pointer and its relative size. This is in contrast to the traditional chasing technique that involves moving a cursor over a moving target and accurately selecting it before it moves out of the way (we refer to this technique as Chase). Pausing the interface theoretically removes the target speed, reducing the movement time of the pointer because the pointer speed no longer needs to be coupled to the target speed. For the same reason, we expect the error rate to reduce. The main adjustment for users is that selection is done with a mouse-up event after mouse movement, which is different from the usual mental model for selection. Our experiment, described next, tests this hypothesis and compares our Hold technique with the usual Chase technique as well as a hybrid of the two to see if users can seamlessly and effectively use a combination of both.

5 Empirical Validation of Moving Target Models

For our model validation, we ran a controlled experiment following the standard protocol used in Fitts' experiment (discrete point-select) for both 1D and 2D where subjects are required to begin with the pointing device at a designated start location and move to within the target with a controlled set of independent variables (selection type, distance, size, velocity, angle and direction). The test environment was structured as a game developed in Flash CS4 called "Catch the Wisp" (based on a previous game created by Ilich[18]) to test the three approaches: Chase, Hold, and Hybrid. In this game the three interaction techniques were abstracted as game objects that we developed as potions. The game mental model was designed through an iterative design strategy to avoid confusion for subjects and establishes a simple analogy that minimizes the training and confounding explanation that you might see in traditional Fitts experiments directly applied to moving targets. The three techniques are:

Chase: The user pursues and selects a moving target by predicting its movement and clicking the left mouse button when the cursor is over it. In state space shown in **Fig. 2**, State 0 represents a Button-Up state with no initial target selection, while State 1 represents a Button-Down state where an object has been selected.

Hold: The user is able to freeze all targets' motion by holding the left mouse button down. With the mouse button depressed, the user can move the cursor over the paused object and release the button to select it. Releasing the button while the cursor is not over a valid target will resume the motion of all targets in view. In state space as shown in **Fig. 2**, State 0 represents a Button-Up state with no initial target selection and the target is in motion; State 1 represents a Button-Down state where the target has been frozen and a subsequent Button-Up event with the cursor over the target will result in target selection.

Hybrid: This model is a hybrid of the previous two models in which the user is free to chase the target and reduce the initial amplitude of movement, until they decide to click, hold the mouse button down and freeze the target for a final precision or corrective phase of movement. In this model, the target can be acquired by either a Button-Up or Button-Down event, provided the cursor is directly over the target. In state space as illustrated in **Fig. 2**, State 0 represents a Button-Up state with no initial target selection and the target is in motion; State 1 represents a Button-Down state where the target has been frozen and selected if the cursor was over the target.

A subsequent Button-Up event with the cursor over the target will also result in target selection.

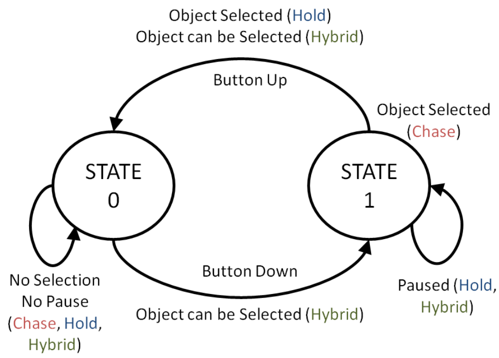

Fig. 2. State Transition Diagram for methods of interaction

The user study consisted of two phases in which we first compare the performance of Chase and Hold, and then observe user behavior in the Hybrid model (Chase-or-Hold) to see if users can effectively use both techniques together seamlessly.

The challenge in creating a test environment for moving targets is that we needed to ensure that we could reliably have the moving targets in a predetermined position across conditions between subjects. Thus, we used a game called "Catch the Wisp" where the target object was abstracted as a *wisp*, or a ball of light from folklore, that would start at a fixed distance from the cursor. In order to make sure that the cursor is at a constant distance from the target, users would have to roll the mouse over a target start location, called a *potion*, in the game metaphor, which is located at a predefined location from the target. Users were presented with three different colors for the start location: red, blue and green representing the three different techniques Chase, Hold and Hybrid, respectively. The behaviour of each potion was framed as part of the game such as paralysis and removing a wisp's shield to provide a mental model consistent with the technique being tested. Using this game, we could observe the acquisition of a variety of targets while the users remained engaged and following instructions without making mode errors with respect to technique.

5.1 Apparatus

The user study was conducted on a Toshiba laptop with a 2.10GHz Core2 Duo CPU with 2GB of RAM running Windows XP Professional. For the purposes of this experiment, "Enhance pointer precision" was disabled and the pointer speed was set to 6 (of 10). The laptop LCD display was used at a resolution of 1280 x 800 pixels at a refresh rate of 60Hz. A Microsoft optical wheel mouse was used as the input pointing device and the Adobe Air environment was set to 1024 x 640 pixels while running the Flash program.

5.2 Participants

Fifteen paid university students, eleven female and four male, participated in the experiment. Participants ranged in ages from 19 to 36, were all experienced computer users and have either normal or corrected to normal vision. None of the participants had color blindness. All participants controlled the mouse in the experiment with their right hand. Participants report playing computer games rarely or never.

5.3 Procedure

Participants played the "Catch the Wisp" game and they were asked to capture a moving wisp using the mouse functions according to the test conditions based on the start location, i.e. *potion,* color. The destination target, i.e. *wisp,* is presented as a white circle protected by a shield which is disabled differently by each technique. For the red potion, by simply rolling the mouse over the potion the shield will be disabled allowing users to capture the wisp by clicking on it; the Chase mode. For Hold, we use a blue potion. When rolling over the blue potion a blue web (24 pixels by 20 pixels) appears at the potion location and by depressing the left button of the mouse over the blue web the wisp's shield will be removed and the motion will be frozen as if paralyzed. Keeping the mouse button down, users can then drag a thread from the web to the wisp and releasing the button over the wisp to catch it. With the green potion, the shield is removed when they roll over it. At that point, users could decide to pursue the wisp and click on it to catch it or if they prefer, they can hold the left button down, freezing the target and displaying a diagonal cross hair where the cursor is. Then, they can drag the diagonal cross hair over the wisp and release the button to catch it. These three methods are shown in Fig. 3 depicting the start mode (left panel) and the selection mode (right panel).

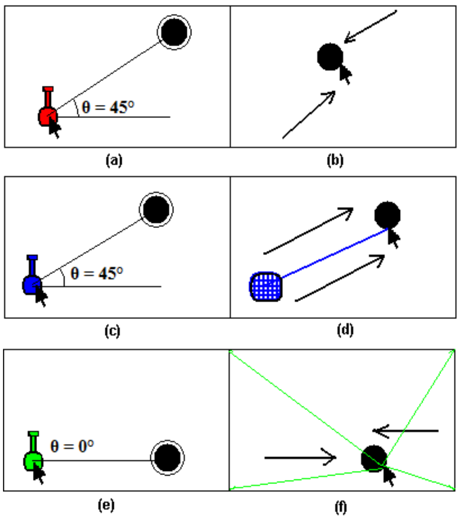

Fig. 3. Experiment Acquisition Types, Red Potion/Chase (a,b), Blue Potion/Hold (c,d) and Green Potion/Hybrid (e,f)

The game was structured as a series of trials, in each trial users were asked to select one moving target which starts moving from a predefined location which is at a constant distance from a start location. In each trial, the target has a constant size and moves at a constant speed along straight lines that bounce off the edges of the screen. Rolling over the start location would activate the corresponding technique causing the start target, i.e., *potion* to disappear and the target (i.e. *wisp*) to start moving. Participants started by completing a tutorial of 24 trials that included on-screen cues showing the next action they have to perform such as "Move the mouse over the potion" or "Click on the web to pause the wisp". After completing the tutorial, participants started the game which consists of sixteen sets (8 red and 8 blue). Each set contains 36 trials, so in total the game has 576 trials. The sixteen sets were organized in alternation of Chase (Red) and Hold (Blue) sets where one type of condition is presented in each set. Upon completion of the Chase/Hold sets, participants would test the Hybrid (Green) condition. They did twelve practice trials with the Hybrid condition. For the experiment, participants completed 72 trials using Hybrid condition that was specified as a bonus set to keep in line with the game metaphor for the experimental set up. For each trial, participants have a maximum of five attempts to select the target after which the trial is ended and they are advanced to the next trial. At the end of each set, a message was displayed informing the participants of the number of targets they caught in that set, the total credit they achieved up to that point and their best acquisition time. Participants were allowed to take breaks after the completion of each set. They were instructed to be as accurate and as fast as possible.

5.4 Experimental Design

The user study was run as two distinct experiments, divided between targets moving in 1D and in 2D since having one subject do both conditions was deemed to take too long. To quantitatively facilitate a comparison of performance between Chase trials and Hold trials a repeated measures within-participant factorial design was used. Selection method determined by the potion color was the independent variable. In order to determine the relation between the task difficulty and acquisition time, we used four other independent factors. These factors are:

Size (W): The size of the wisp in each trial, as measured by the radius of its circle in pixels. The three level used are: 10 pixels, 18 pixels or 30 pixels.

Speed (V): The constant speed at which each wisp traveled. Three levels were used:100 pixels/sec, 175 pixels/sec or 250 pixels/sec.

Direction: The direction of the wisp from the potion. We used two levels: toward or away from the potion.

Movement Angle (θ): The angle between wisp and cursor. The angles are: 0 and 180 degrees in 1D and 45, 135, 225 and 315 degrees in 2D relative to a horizontal axis through the center of the potion.

These factors were fully counter-balanced between trials. Within each selection method, participants in the 2D experiment tried 3 x 3 x 2 x 4 conditions in which they carried out 4 targeting trials for each condition. While participants in the 1D experiment tried 3 x 3 x 2 x 2 conditions in which each condition was carried out 8 times. Therefore, for each dimension participants were presented with 576 trials distributed evenly between two selection techniques, including 288 Chase and 288 Hold. In order to compare the results with the traditional Fitts tasks, different sizes were used while keeping the distance to the target constant. Varied speeds of movement were used to determine their effects on the index of difficulty of moving targets. Finally, we considered that objects moving away from the cursor may be easier (or harder) to select than objects moving towards the cursor so had trials for each to test this.

For the second phase of the experiment where participants used the Hybrid method (green potion), a qualitative measure was used to observe their acquisition behavior. In this phase, participants had the option to pursue the target, freeze the target or a combination of both in order to select the moving target. In this phase, we were looking to see whether subjects optimize the two since allowing a target that is moving toward you while you move towards it may achieve faster target acquisition times versus pausing it; however, it may come at the price of accuracy as well as poorer time performance if you miss on the first rendezvous with the target.

5.5 Performance Measures

For this study we used the acquisition time and the number of errors as our dependent variables. The acquisition time MT was measured from the time the start location (i.e. potion) was activated, when the mouse rolled over it, until the time the moving target was captured. The number of clicks or mouse up events that did not result in a moving target's capture were counted as errors. Moreover, the position of the cursor and the moving target were recorded every frame. Every time a participant froze the target was also recorded with the total acquisition time in order to study participant behavior.

For the Hybrid set, a qualitative analysis consisted of a statistical measure of the distribution of participant behaviors among four categories:

Chase: A participant chose to pursue the target without freezing it.

Hold: A participant chose to freeze the target immediately after the activation of the start location.

Hybrid: A participant chose to start pursuing the target and then freeze the target closer to it.

Error Correction: A participant missed the target and tried to correct their miss.

We categorized each trial into one of the above four categories according to:

- If the trial had an error then it is categorized as an Error correction.
- Else if a participant did not Hold during the trial then a Chase behaviour was selected.
- Else if a participant did Hold then we checked the cursor position when the last Hold event occurred with the initial cursor and wisp position.
  - If the distance moved was less than the remaining distance to the wisp then it was considered to be a Hold behavior.
  - Else it was a Hybrid behavior.

5.6 Results

Both a repeated measures ANOVA analysis and a Generalized Linear Mixed Models (GLMMs) Test were carried out to test the significance of the results. We illustrate below the GLMMs Test results since our data does not have a normal distribution where it is positively skewed. We get almost similar significant effects in both. Selection technique, size, speed, angle and direction were taken as fixed factors in the GLMMs Test while subject and trials were taken as random factors. The outliers were removed based on the acquisition time and number of errors, such that any data point with extreme acquisition time where its frequency dropped to zero, or with 5 errors (since subjects were allowed to have only 5 attempts in each trial) were not included. In total, 0.45% of the 1D data and 0.90% of the 2D data were removed as outliers. Six subjects participated in the 1D selection task experiment, and nine subjects participated in the 2D selection task experiment.

1D selection task

Phase 1: Our data was positively skewed so we used a Generalized Linear Mixed Models (GLMMs) test to analyze the dependent variable acquisition time. The analysis showed that the independent variables selection technique ($F(1, 3099.89) = 260.26$, $p < 0.001$), size ($F(2, 3099.38) = 301.26$, $p < 0.001$), speed ($F(2, 3099.38) = 5.02$, $p = 0.007$), direction ($F(1, 3099.27) = 6.08$, $p = 0.014$), and angle ($F(1, 3099.37)$

= 101.36, p < 0.001) had a significant effect on the acquisition time. Moving to the left (θ = 180) was found faster than moving to the right (θ = 0) for both techniques. Post-hoc comparison showed that the mean acquisition time for Hold (M = 981.838, SD = 69.015) was longer than Chase (M = 835.525, SD = 63.931). This coincides with participants' feedback that the blue potion (Hold) gives them the impression of having enough time to select the target and they do not have to rush as in red potion (Chase) trials. Hence, it slowed their reaction and took a longer time to get started after rolling over the potion. Also technique x size x speed x angle interaction showed significant effect (F(4, 3099.31) = 3.94, p = 0.003) on time. The overall mean acquisition times for techniques by size, speed, angle and direction are illustrated in Fig. 4(i).

Errors were also analyzed using the same GLMMs test as acquisition time. A significant effect was observed on the number of errors for the selection technique (F(1, 3105.66) = 380.17, p < 0.001), size (F(2, 3101.72) = 17.35, p < 0.001), speed (F(2, 3101.69) = 3.33, p = 0.036) and angle (F(1, 3101.61) = 23.34, p < 0.001). Direction (F(1, 3100.85) = 0.182, p = 0.67) had no main effect on the number of errors. Chase contained more errors (M = 0.073, SD = 0.76) compared with Hold (M = 0.015, SD = 0.36) which illustrated the speed accuracy trade off in the two selection techniques consistent with users feeling they had to rush in the Chase mode.

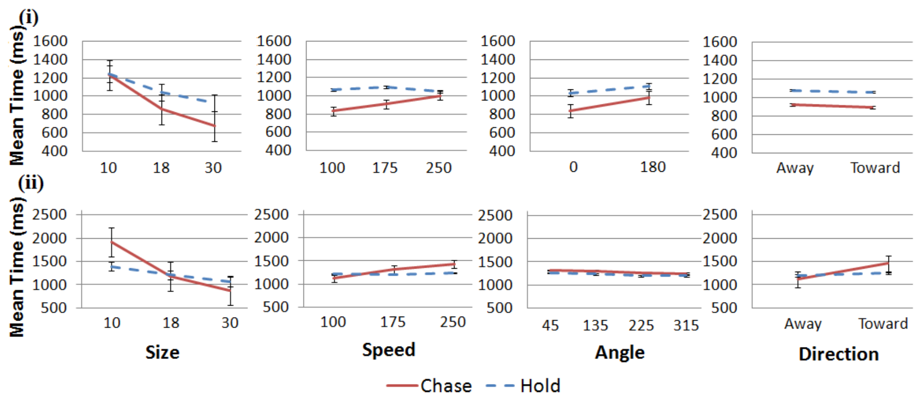

Fig. 4. The effect of size, speed, angle and direction on mean acquisition time for (i) 1D and (ii) 2D

Phase 2: The 72 trials of the green potion were compared with the last 72 trials from each technique of the first phase of the experiment using the GLMMs Test. A significant effect was observed on acquisition time (F(2, 272.09) = 10.49, p < 0.001). Hybrid (M = 842.68, SD = 420.49) was faster than Hold (M = 1056.67, SD = 475.18) and Chase (M = 960.67, SD = 859.28). Moreover, a significant effect was observed on the number of errors (F(2, 267.21) = 35.15, p < 0.001). Hold (M = 0.017, SD = 0.397) had fewer errors than either Chase (M = 0.089, SD = 0.827) or Hybrid (M = 0.082, SD = 0.995).

2D selection task

Phase 1: For the 2D selection task experiment, GLMMs was conducted to compare the total acquisition time for each technique. There was a significant effect (F(1, 4807.93) = 64.38, p < 0.001) when an overall comparison was made and the mean acquisition time for Hold (M = 1239.874, SD = 67.079) was shorter than Chase (M =

1450.053, *SD* = 127.114). The other independent variables size (F(2, 4807.58) = 668.66, p < 0.001), speed (F(2, 4807.30) = 65.50, p < 0.001), direction (F(1, 4807.14) = 156.26, p < 0.001), and angle (F(3, 4807.16) = 4.66, p = 0.003) showed significant effect on acquisition time. Pair-wise contrast between angles showed a significant difference between angle pair 45 and 315 degrees and this coincides with results found in [28]. This effect is most likely due to the fact that targets on either end of a vector are equally difficult to select and movement direction had no effect on acquisition time as illustrated in [12]. The effect of the angle on acquisition time was dependent on both size and direction indicated by the interaction size x direction x angle (F(6, 4807.15) = 2.24, p = 0.037), and also mode, size, speed and direction indicated by mode x size x speed x direction x angle (F(12, 4807.14) = 2.29, p = 0.007).The mean acquisition times for technique by size, speed, angle and direction are illustrated in Fig. 4(ii). In addition, significant effects were observed for size and speed combinations; however, Hold exhibited a lower mean acquisition time for the small target as well as the fast moving targets as shown in Fig. 5.

A significant effect of technique was also observed on the number of errors (F(1, 4812.41) = 754.92, p < 0.001), Hold contained fewer errors (*M* = 0.009, *SD* = 0.014), compared with Chase (*M* = 0.083, *SD* = 0.098). The main effect of size (F(2, 4810.50) = 277.73, p < 0.001), speed (F(2, 4808.88) = 56.68, p < 0.001) and direction (F(1, 4808.01) = 5.56, p = 0.018) also found to be significant. However, angle showed no significant main effect on errors.

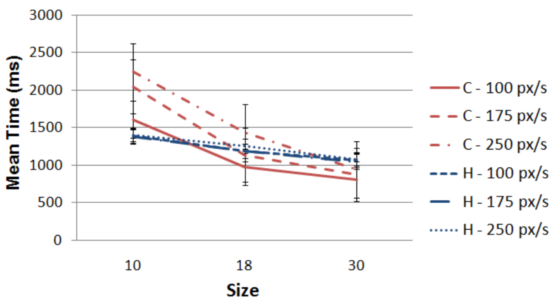

Fig. 5. The 2D mean time by size and speed for Chase and Hold

Phase 2: A GLMMs test was also conducted to analyze the 72 trials of the 2D Hybrid method. A significant effect was observed on acquisition time (F(2, 291.23) = 8.98, p < 0.001). Hybrid (*M* = 1162.07, *SD* = 635.63) was faster than Hold (*M* = 1198.16, *SD* = 499.15) and Chase (*M* = 1333.09, *SD* = 1343.40). Moreover, a significant effect was observed on the number of errors (F(2, 97.46) = 55.82, p < 0.001). Hold (*M* = 0.01, *SD* = 0.306) had fewer errors than either Chase (*M* = 0.096, *SD* = 0.96) or Hybrid (*M* = 0.054, *SD* = 0.76).

5.7 Model Fitting

By a least-squares fit method, we estimated the coefficients of the models described earlier for Chase and Hold. We adopted the original Fitts' Law [11] in Equation 1 for trials involving Hold in 1D while we tested Equations 11 and 12 for Hold trials in 2D. For trials involving Chase in 1D, we adopted Equation 10 while Equations 13 and 14 were adopted for trials in 2D. For 1D targets, the Fitts' model (R^2 = 0.9869) and ID_{C1} (moving away R^2 = 0.9662, moving toward R^2 = 0.9755) have shown good fits with the experimental data. The ID_{P2} (R^2 = 0.9717) and $ID_{WtW'\theta}$ (R^2 = 0.9505) models for stationary targets in 2D have also shown an excellent fit with the experimental data of Hold.

For 2D moving targets models, the $ID_{VWtW'\theta}$ (R^2 = 0.9099) showed a good correlation with the data while the ID_{C2} model exhibited poor correlation with some angles. The poor correlation can be explained as discussed earlier that angle pairs (45, 225) and (135, 315) lay in the same diagonal vector. As in previous research each pair was considered as one movement angle and this was shown in [28] where a significant difference existed only between angles 45 and 315. When each pair was considered as one movement angle, the correlation got better (R^2 = 0.9027) and it exhibited similar performance as the $ID_{VWtW'\theta}$. Another factor could be the target dimension, the ID_{C2} model gives different weights for width and height of the target, however, we used a circular target in our experiment where both height and width are equal. Fig. 6 illustrates the average acquisition time versus the index of difficulty for both $ID_{VWtW'\theta}$ and ID_{C2} models.

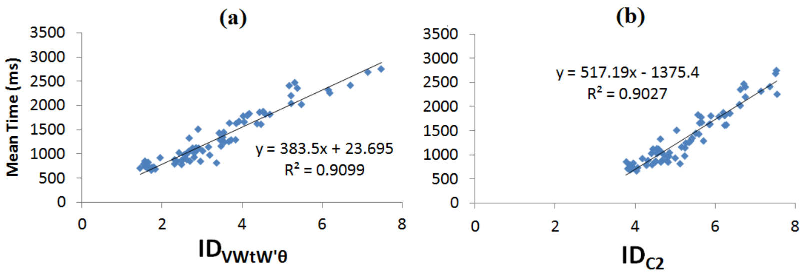

Fig. 6. Mean Acquisition Time Vs. Index of difficulty for Chase in 2D using (a) $ID_{VWtW'\theta}$, and (b) ID_{C2} models

6 Discussion

For 1D we observed from the first experiment that Chase exhibited lower acquisition time than Hold in all conditions. This trend can be interpreted in different ways. The overhead of clicking on the web and sustaining the dragging motion outweighed the benefit of freezing the target. In addition, as the target is frozen it gives an illusion of the time also being paused. In this state, subjects did not rush in selecting the target resulting in taking longer. Adding a score in the game based on time taken, target size and speed does not help some users in mitigating this effect. Adding a time limit to capture a target as some subjects suggested, would help we think. Questionnaire results, that subjects filled after the experiments, agreed with these findings. Subjects preferred Chase as they felt it was faster and they did not account for the accuracy. Also subjects tended to take a longer time to precisely release the button over the target in Hold which resulted in fewer errors but longer acquisition time.

However, for 2D Hold showed faster acquisition time for conditions involving a target size of 20px (small) as well as conditions involving a target speed of 175px/s (moderately fast) and 250px/s (fast). This contradicts results for the selection task in 1D. We believe that this can be explained by the distance the target had to travel was restricted to a horizontal path in 1D. Because of this restriction in 1D, the target was more likely to rebound off the end and approach the cursor while in 2D the target moves in an angle and thus would take longer time to hit a wall and rebound towards the cursor again for users to take advantage of that. We confirmed that speed has little impact on Hold as observed in Fig. 4. In both 1D and 2D, subjects sacrificed accuracy for speed in Chase by attempting to click on the target in rapid succession. While they sacrificed speed for accuracy in Hold by carefully positioning the cursor over the target before releasing the mouse button.

The results of the second phase of the experiment in 1D showed that Hybrid resulted in reduction in acquisition time of 12% over Chase and 20% over Hold. While in 2D, it showed a reduction of 13% over the Chase and 3% over the Hold suggesting subjects are performing optimization seamlessly. The mouse and target position logs for each subject were analyzed to categorize the technique used for each trial. The results are summarized by the percentage of trials for which each technique was chosen by target size, speed, angle, and direction in Fig. 7. In 2D, subjects tended to use a Hybrid approach more often while in 1D, subjects tended to use Chase as they thought it is faster. Subjects in the 1D experiment commented that they had used Chase more often in the second phase due to the unfamiliarity with Hybrid and they claimed that Chase is faster which would optimize their acquisition time.

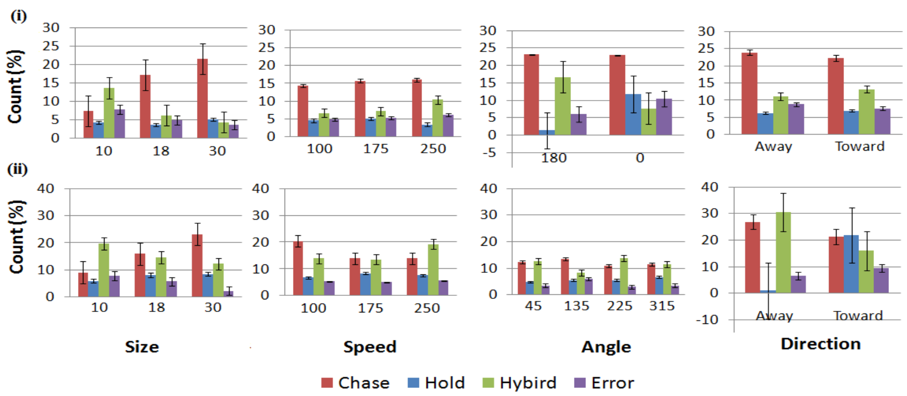

Fig. 7. Technique chosen by size, speed, angle, and direction in (i) 1D and (ii) 2D

The distribution of the ratios (Chase /(Chase + Hold)) and (Hold /(Chase + Hold)) for the second phase of the experiment was also analyzed and it is summarized by target size, speed, angle, and direction in Fig. 8. Users tended to chase the target most of the time across the different conditions. However they froze the target more often as the target gets smaller and faster which indicates a seamlessly and effectively use of techniques.

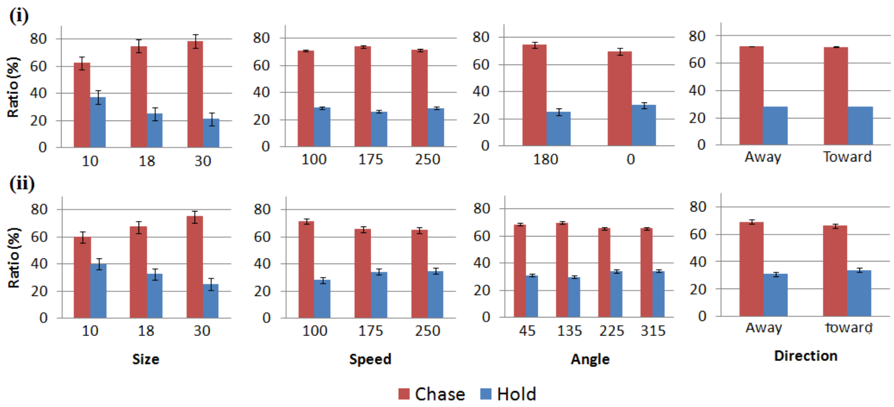

Fig. 8. The ratio distribution of Hold and Chase using Hybrid in (i) 1D and (ii) 2D space.

7 Conclusion and Future Work

We performed studies evaluating three selection techniques for moving targets and investigated the effect of target size, speed, movement angle, movement direction and their interactions on acquisition performance in both 1D and 2D. In 2D, our Hold method provides faster and more accurate selection performance for small or fast moving targets. Building upon prior work on 1D and 2D selection tasks, we introduced and validated variants of Fitts' Law that model selection of moving targets in both 1D and 2D. We have shown that performance time for moving targets in 2D can be predicted for most situations using our models. For some variants of angles the correlation is not as accurate as we would like, motivating further studies to test various angles and adjust the model. The work we have presented has been validated for linear movement and mouse as input device which provides a foundation for future research and validation of pointing models for chaotic targets and other input devices (e.g. finger). We anticipate Hold will work well for complex movement types since a less predictable motion is more difficult to select with Chase. Moreover, we think the chase technique will be disadvantaged for touch due to the repetition of tapping, lifting required when a selection fails; such as when trying to select small, fast moving targets. However, we believe Hybrid would work well because one touch anywhere pauses the video and users just need to slide their finger to the target. Thus, if the first touch misses, keeping the finger down and sliding it to the target will allow easy correction. We suspect that users will optimize the selection time by approaching the target for a rendezvous before touching the display. Further, we also foresee that rapid aimed movements, such as moving target selection maybe a hybrid of an iterative correction model and an impulse variability model [25], suggesting a new area for future research. The first movement towards the target could be considered as an impulse task, where user tries to hit the target within a specific time in their mind, while the next moves are corrective movements. Thus, a hybrid model of Fitts' law [11] and Schmidt's law [26] may be an effective way to characterize rapid aimed movements.

Moving targets are likely to be common in future interfaces and in these environments accuracy is generally more important than speed. We have shown that our Hold and Hybrid approaches provide an effective interaction technique that can be easily integrated into interfaces with moving targets.

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