INSTANTANEOUS TARGET SELECTION WITH 2D SACCADES: CASE STUDY

THESIS

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Do Hyong Koh, B.E.

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INSTANTANEOUS TARGET SELECTION WITH 2D SACCADES: CASE STUDY

Committee Members Approved:

Oleg V. Komogortsev, Chair

Young Sam Ryu

Carl J. Mueller

Approved:

J. Michael Willoughby
Dean of the Graduate College

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ABSTRACT

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Do Hyong Koh, B.E.

Texas State University-San Marcos

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SUPERVISING PROFESSOR: OLEG V. KOMOGORTSEV

We introduce and evaluate a new Instantaneous Saccade (IS) selection scheme for eye gaze driven interfaces where the speed of the target selection is of utmost importance. In the IS selection scheme, target selection occurs at the start (onset) of a saccade requiring only constant amount of time to be completed. The IS performance is compared to the conventional Dwell Time (DT) selection scheme where target selection is triggered when a user fixates on an object for a certain amount of time. The IS method is also compared to the Saccade Offset (SO) selection scheme where target selection occurs at the end of a saccade. The IS scheme is compared to the Hybrid Saccade (HS) selection where DW selection is triggered when IS selection fails. All four schemes were evaluated in terms of the throughput of input performance, task completion time, and the error rate in multi directional target selection task with three different target distance level. All four schemes were also tested in term of completion time and error rate in an eye-gaze

guided game. Results show that the Instantaneous Saccade selection was approximately more than 50% faster than the DT selection to complete a task in any target distance level. In terms of throughput comparison, the throughput of the IS selection is about 7% greater than the throughput of DT selection in any target distance level. We hypothesize that Instantaneous Saccade selection will be beneficial in gaming environments that require very fast interaction speeds.

CHAPTER I

INTRODUCTION

Today's video games incorporate innovative and intuitive interaction techniques such as motion sensing, voice recognition, and facial recognition to give users a more exciting experience. Recently, Microsoft introduced their new gaming accessory named Kinect which provides full body tracking along with voice and facial recognition in 2010 E3 expo (E3, 2010). It is interesting fact that no controller will be needed for the game for the future. However, eye movement recognition has not been applied to video game controls. We want to emphasis that the eye tracking is also important for the no controller gaming environment. Eye-gaze guided interaction techniques have recently attracted research interest, and most of them were to use eye-gaze as an input modality for users with disabilities (Istance et al., 1992; Koh et al., 2009; Komogortsev & Khan, 2007; Kummar & Winograd, 2007; MacKenzie & Zhang, 2008; Nakayama & Takahasi, 2008; Tien & Atkins, 2008). Smith and Graham (2006) explored the use of eye-gaze interaction for video game control. They concluded that an eye-gaze guided interaction can provide new experiences for video game users. The types of games they applied included a first-person shooter game, a role playing game, and an action/arcade game.

To enable eye-gaze guided interaction, the raw eye position signal must be identified and analyzed. Parts of the signal are classified into meaningful components such as fixations (movements that occur when gaze is dwelling on objects), saccades (movements between two separate fixations), and pursuits (movements that occur when eyes are tracking moving objects). Fixations occur when the duration of an eye fixation reaches a predefined threshold and they are the most common modality used for an eye-gaze guided interaction (Kumar et al., 2007; Miniotas et al., 2004; Morimoto et al., 1999). However, very little attempt has been made to employ saccades for the eye-gaze guided interaction (Urbina & Huckauf, 2007). Pursuit-based interaction seems unexplored yet in the HCI community.

To classify eye movement, there are several models including the most commonly used Velocity-based Threshold (I-VT) model (Salvucci & Goldberg, 2000). I-VT model is used often because of the ease of implementation and low computational cost. However, the model is not robust and not capable of handling high levels of noise in eye position data.

Kalman Filter is a recursive estimator that computes a future estimate of the dynamic system state from a series of incomplete and noisy measurements. Eye trackers frequently fail to report eye position data, and the reported data are susceptible to noise due to the individual anatomical properties of users and limited spatial resolution of the equipment. Therefore, a Kalman Filter framework can be used to provide more accurate and robust estimation of the eye position signal. At the same time, the Kalman Filter is capable of classifying eye movements (Sauter et al., 1991). Komogortsev and Khan (2007) were the first ones to discuss the use of the Kalman Filter in a real-time eye-gaze guided computer interface, and they have indicated that the filter can be successfully used during eye-tracking failures. Kumar et al. (2008) presented the case where a Kalman Filter provided smoothing to a raw eye position signal, thereby increasing the stability of the input. Koh et al. (2009) provided a comprehensive evaluation of the interface performance driven by a Kalman Filter. They showed that the Kalman Filter for the eye gaze interface provided better performance than using the I-VT model (Koh et al., 2009).

Researchers have introduced interaction schemes that go beyond the realm of interaction based on Dwell Time. Blanch and Ortega (2009) introduced a rake cursor interaction technique that combines mouse controlled selection and cursor activation by eye-gaze. Spakov and Miniotas (2005) developed a target expansion scheme during real-time eye tracking calibration. In addition, Miniotas et al. (2004) evaluated target expansion during tasks controlled by eye-gaze. Salvucci and Anderson (2000) present an intelligent gaze-added interface that uses a probabilistic algorithm. One of the goals of those methods was to improve the accuracy and ease of selection.

The Instantaneous Saccade (IS) selection method that we are proposing in this paper is designed for the eye-gaze driven HCI systems that require extreme interaction speeds. In the most common eye gaze driven systems, interface component selection uses Dwell Time (DT) methods that involve data buffering for at least 100 ms (Kumar et al., 2007; Morimoto & Ihde, 1999; Sibert & Jacob, 2000). In such interfaces, the duration of the detected fixation initiates a “click”. The goal of the selection method is to make a selection as soon as the eye movement to a new target is detected. Fixation-based selection necessitates data buffering and therefore introduces a delay in the system. Future pursuit-based selection methods may require some data buffering for pursuit detection. Here, we are interested in extreme interaction where the speed of “clicking” a target is of utmost importance. Urbina and Huckauf (2007) utilized saccade selection for typing. In that scheme, a component of a pie-like menu was selected when a saccade crossed the outer border of a slice. Also, pie dimensions did not vary, and the landing point of a saccade was not important.

In this work, we are specifically interested in an interaction scheme where the landing point of a saccade is important and indicates the coordinates of a target to be selected. Therefore, target selection is performed by a saccade trajectory prediction model. The saccade trajectory prediction model includes saccade onset detection, saccade direction detection, and saccade amplitude prediction model. The resulting IS selection method is free of buffering delay and independent of the distance to the target.

To explore the benefits of saccade based selection schemes, we introduce and evaluate another interaction scheme called a Saccade Offset (SO) Selection. In the SO selection scheme, selection is triggered at the offset of a saccade (the moment when the saccade ends). In other words, SO selection can be considered as a DT selection without Dwell Time threshold. We also introduce Hybrid Saccade (HS) selection which combines DT selection and IS selection. In HS selection, DT selection is triggered when IS selection fails.

The primary motivation for the IS selection is to provide a new interactive experience that improves the speed of a target selection. For example, IS selection can provide a more exciting experience to users when they are playing first-person shooting games, which require extreme reaction speeds. More specifically, the IS selection can provide an exciting experience in multiplayer games such as World of Warcraft (2009), where players compete in a hostile environment and accumulation of each saved millisecond might increase the chance of victory. Based on the findings provided in this paper, the IS selection does provide higher throughput and task completion times in a special case of the eye-gaze guided games. Theoretical evaluation of the IS scheme indicates 45% improvement in selection speed, while practical results indicate the 28% improvement.

To summarize, this paper contains three logical parts 1) theoretical evaluation of the time it is possible to save with IS target selection 2) theoretical feasibility of IS approach 3) practical application of the IS approach.

CHAPTER II

THEORETICAL EVALUATION: IS SELECTION

Selection Time Savings

The goal of Instantaneous Saccade-based (IS) selection is to select a target at a beginning of a saccade. It is important to compare IS selection to two other eye-movement-based selections: Dwell Time (DT) and Saccade Offset (SO) selection. In the DT selection, selection happens when the user fixates on the target for the amount of time specified as the DT Threshold (usually this value is 100ms. or greater). Saccade Offset (SO) selection occurs at the end of a saccade, i.e., as soon as the user's eye gaze lands on the target. Therefore, the SO selection is triggered faster than the DT selection. Figure 1 illustrates DT, SO, and IS.

General formula for estimation on the amount of time that can be saved by a faster selection scheme over a slower selection scheme can be estimated by the formula:

$$\mathrm{T_{saved}} = 100 \cdot \left(1 - \frac{\mathrm{T_{S1}}}{\mathrm{T_{S2}}}\right) \tag{1}$$

where $\mathrm{T_{S1}}$ is the selection time of a faster scheme S1 and the $\mathrm{T_{S2}}$ is the selection time of a slower scheme S2.

Selection time of the DT-based target selection can be computed by the following formula:

$$T_{DT} = T_{tar\_acq} + T_{sac\_dur} + T_{dwell\_time} \quad (2)$$

T_{tar_acq} is the amount of time the brain requires to calculate the neuronal control signal for extra-ocular muscles to rotate the eye globe. Usually, the target acquisition time is around 200ms due to the delays in Human Visual System (HVS) (Leigh & Zee, 2006). T_{sac_dur} is a duration of a saccade that lands the eye on the target. It is possible to compute saccade's duration based on its amplitude with the following formula (Carpenter 1977):

$$T_{sac\_dur} = 2.1 \cdot A_{sac} + 22 \quad (3)$$

where A_{sac} is saccade's amplitude measured in degrees.

The SO target selection can be estimated as:

$$T_{SO} = T_{tar\_acq} + T_{sac\_dur} \quad (4)$$

The IS target selection can be estimated as:

$$T_{IS} = T_{tar\_acq} + \frac{k}{f} \quad (5)$$

f is the sampling frequency of the eye tracker, and k is the number of eye position samples needed for saccade amplitude prediction, therefore, $\frac{k}{f}$ is the amount of time in seconds that is required to predict the amplitude of a saccade.

Once the potential in terms of the time savings is estimated it is important to achieve two goals to make IS target selection possible: saccade's amplitude prediction and saccade's direction prediction. Following section describes theoretical approach to discuss if such prediction is possible.

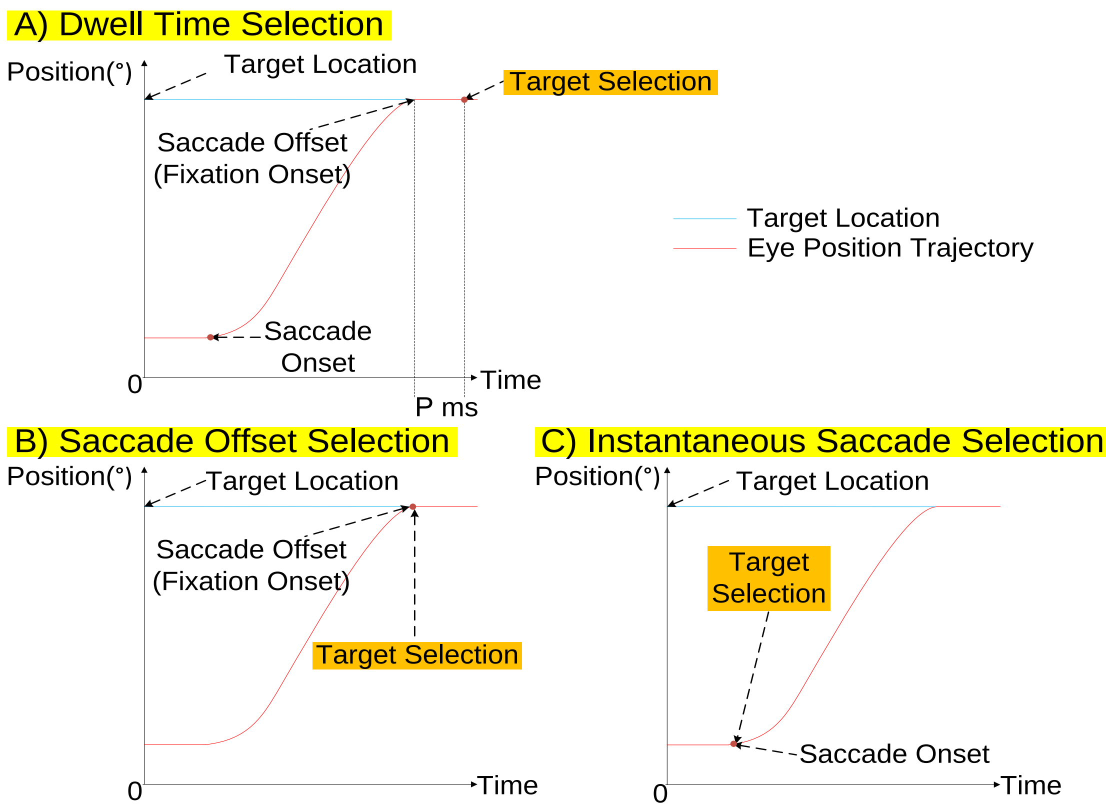

Figure 1. Eye Movement Based Target Selections. a) Dwell Time b) Saccade Offset c) Instantaneous Saccade.

Saccade's Trajectory Prediction by Oculomotor Plant Mathematical Model and Kalman Filter

Two Dimensional Oculomotor Plant Mathematical Model

Two dimensional linear homeomorphic oculomotor plant model (2D-OP) is capable of simulating eye movements including saccades by considering physical properties of the eye globe and four extraocular muscles: medial, lateral, superior, and inferior recti. The 2D-OP mathematically represents dynamic properties of the OP via a set of linear mechanical components such as springs and damping elements. Specifically following properties are considered: active state tension – tension developed as a result of the innervations of a muscle by neuronal control signal, length tension relationship – the relationship between the length of a muscle and the force it is capable of exerting, force velocity relationship - the relationship between the velocity of a muscle extension/contraction and the force it is capable of exerting, passive elasticity – the resisting properties of a muscle not innervated by the neuronal control signal, series elasticity – resistive properties of a muscle while the muscle is innervated by the neuronal control signal, passive elastic and viscous properties of the eye globe due to the characteristics of the surrounding tissues. Neuronal control signal command that is sent by the brain to the extraocular muscles in a form of the neuronal discharge is approximated as a pulse-step signal where step part of the signal determines the eye position prior and after the saccade and pulse part of the signal determines saccadic amplitude. More detailed description of these properties can be found in (Komogortsev and Khan 2008). The 2D-OP employs the OP properties that are contributing to the horizontal and vertical component of the eye movement, describing dynamics of the eye globe's rotation via twelve differential equations (Komogortsev and Jayarathna 2008). As a result 2D-OP is capable of simulating accurate saccadic signal on the two dimensional plane, therefore allowing to estimate all the OP properties contributing to the eye rotation. Consequently, the 2D-OP has higher potential in producing more accurate identification results due to the more accurate representation of the OP with larger number of anatomical components included in the model.

Two dimensional linear homeomorphic representation of the OP is beneficial because a) it is able to produce 2D eye movement signal (projection of the line of sight on a computer screen) with characteristics of normal humans, therefore allowing for a close match between the simulated and the recorded signal, b) it contains the representation for the major anatomical components of the OP, allowing to estimate those components from the eye movement trace, c) it has linear design speeding up the estimation procedure for OP properties.

Kalman Filter

The Kalman Filter is a data processing algorithm that predicts a future estimate of the dynamic system state with existence of incomplete and error signals. A Kalman Filter minimizes the error between the estimated and actual values of a system's state. Only the estimated state from the previous time step and the new measurements are needed to compute the new state estimate. Many real dynamic systems do not exactly fit this model; however, because the Kalman Filter is designed to operate in the presence of noise, an approximate fit is often adequate for the filter to be quite useful (Brown & Hwang, 1997). Brown and Hwang (1997) describe the general mathematical framework of the Kalman Filter. In our implementation, Identification by the Kalman Filter models an eye as a system with two states: position and velocity. The acceleration of the eye movement is considered to be white noise with known maximum acceleration.

Saccade Onset Detection with Kalman Filter

To be able to predict future saccade's amplitude it is first important to detect the onset of a saccade. It is possible by creating a two state Kalman Filter with one state representing the position and the second state representing the velocity. The acceleration of the eye movement is considered to be white noise with known maximum acceleration. Komogortsev and Khan (2007) have presented the details of the Kalman Filter parameterization that we have employed in this work.

A Chi-square test monitors the difference between predicted and observed eye-velocity:

$$\chi^2 = \sum_{i=1}^{p} \frac{\left(\hat{\dot{\theta}}_i^- - \dot{\theta}_i\right)^2}{\delta^2} \qquad (6)$$

where $\hat{\dot{\theta}}_i^-$ is the predicted eye velocity computed by Kalman Filter and $\dot{\theta}_i$ is the observed eye velocity computed with the eye position signal from the eye tracker. δ is the standard deviation of the measured eye velocity during the sampling interval under consideration. Once a certain threshold of the χ^2 statistic is achieved, a saccade is detected. It was reported that the filter stability improves if δ is selected to be a constant (Komogortsev & Khan, 2007). Empirical evaluation has indicated that values of $\delta^2 = 1000$ and p=5 provide acceptable performance. The value of the χ^2 threshold was empirically selected to be 5.

Saccade Amplitude Prediction

The 2D-OP model provides a unique opportunity to research the properties of the eye movement signal and create a theoretical model that is capable of accurately predicting saccade's amplitude. When the Two State Kalman Filter is applied to the horizontal and vertical components of the saccade's trajectory resulting chi-square test signal has a distinct shape represented by two peaks in the horizontal and vertical component of movement. Figure 3 illustrates the phenomenon.

Such behavior of the chi-square test presents a unique signature for saccades of any amplitude. Specifically, the Chi-square test signal peaks twice over the course of a saccade. The time of the first peak, counting from the onset of a saccade, stays in the range of 9-13ms (M=11.89ms, SD=1.01) for a saccade range of 1-40° and does not depend on saccade's amplitude. The second peak occurs closer to the end of a saccade.

The height of the first peak closely correlates with the amplitude of the future saccade. Using the 2D-OP model we simulated 3640 saccades with amplitudes ranging from 1-40 ° and tilted to 0-90 °, therefore covering all possible combinations of saccades starting from the primary eye position. Figure 2 presents the result of this simulation.

Employing linear regression technique, it is possible to create a formula (7) that connects the chi-square test value at first peak with the amplitude of a future saccade.

$$A_{sac} = -0.002815 \cdot {\chi^2}^2 + 0.7336 \cdot \chi^2 - 3.494 \qquad (7)$$

A_{sac} is an amplitude of a saccade and χ^2 is the chi-square test value at the first signal peak. Equation (7) provides R^2=0.98 fit to the data received as a result of the simulation.

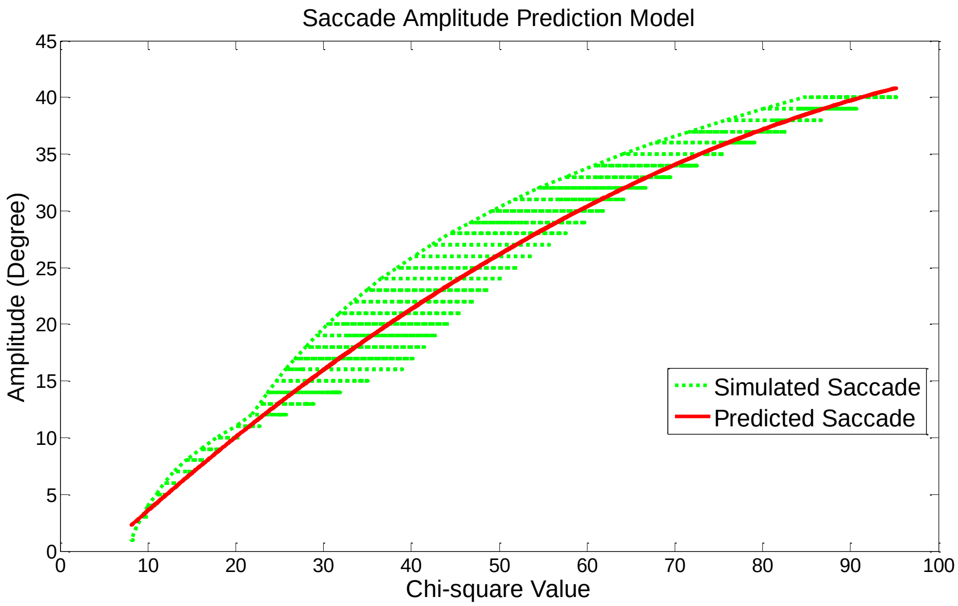

Figure 2. Saccade Amplitude Prediction Model.

Saccade Direction Prediction

Prediction of the future saccade's direction in 2D is a much more challenging task then the horizontal case. In the Cartesian coordinate system, the direction between two points can be obtained by finding the direction of the vector, $(x' - x) + (y' - y)i$, computed with the following formula

$$\mathrm{Dir}_{sac} = \tan^{-1}(\frac{y' - y}{x' - x}) \tag{8}$$

where Dir_{sac} is saccade's direction measured in degrees, (x, y) the coordinates of the saccade's onset, and (x', y') the coordinates of the point at which saccade's direction has to be determined.

The relationship between the first peak created by the first chi-square test peak and the direction prediction represented by the formula (8) create the basis for the IS target selection.

Formulas (7) and (8) present the ideal theoretical case, the actual signal from the eye tracker is noisy (Duchowski 2007) and might not have the high sampling frequency of 1000Hz. Therefore it is important to investigate theoretically, the signal of the lower sampling frequency with noise interjected into the signal.

Lower Sampling Rate and Noise Injection

To test lower sampling case we decided to consider a sampling frequency of 120Hz. 120Hz is de-facto frequency today for major vendors (Tobii, 2009), therefore we decided to this sampling frequency in our theoretical evaluation. The noise present in the eye tracker can be approximated via precision of the equipment - minimum amount of the rotation or the eye globe that the eye tracker can recognize. We decided to consider a more liberal number of 0.05° that is considerately smaller than the number reported by the vendors. Figure 3 illustrates the chi-square test signal behavior during a saccade in three cases : a) sampling frequency 1000Hz, white noise added b) sampling frequency 120Hz, no noise c) sampling frequency 120Hz, white noise added with amplitude of 0.1°

Four cases illustrated by the Figure 3 allow creating tree equations connecting the peak of the chi-test signal to the amplitude of the future saccade.

Following presents 1000Hz sampling frequency case, without noise.

$$\mathrm{A_{sac}} = -0.002815 \cdot {\chi^2}^2 + 0.7336 \cdot \chi^2 - 3.494 \qquad (9)$$

Equation (9) provides R^2=0.98 fit to the data received as a result of the simulation

Following presents 120Hz sampling frequency case, with no noise.

$$\mathrm{A_{sac}} = -2.011 \cdot 10^{-6} \cdot {\chi^2}^2 + 0.01715 \cdot \chi^2 + 3.967 \qquad (10)$$

Equation (10) provides R^2=0.98 fit to the data received as a result of the simulation

In case of 120Hz only one peak exists. The time of the peak, counting from the onset of a saccade, stays in the range of 48-64ms (M=56 ms, SD=8) for a saccade range of 1-40° and does not depend on saccade's amplitude.

Theoretical evaluation provides an estimate of the expected performance of the IS, but it is important to evaluate IS performance in terms of practical application.

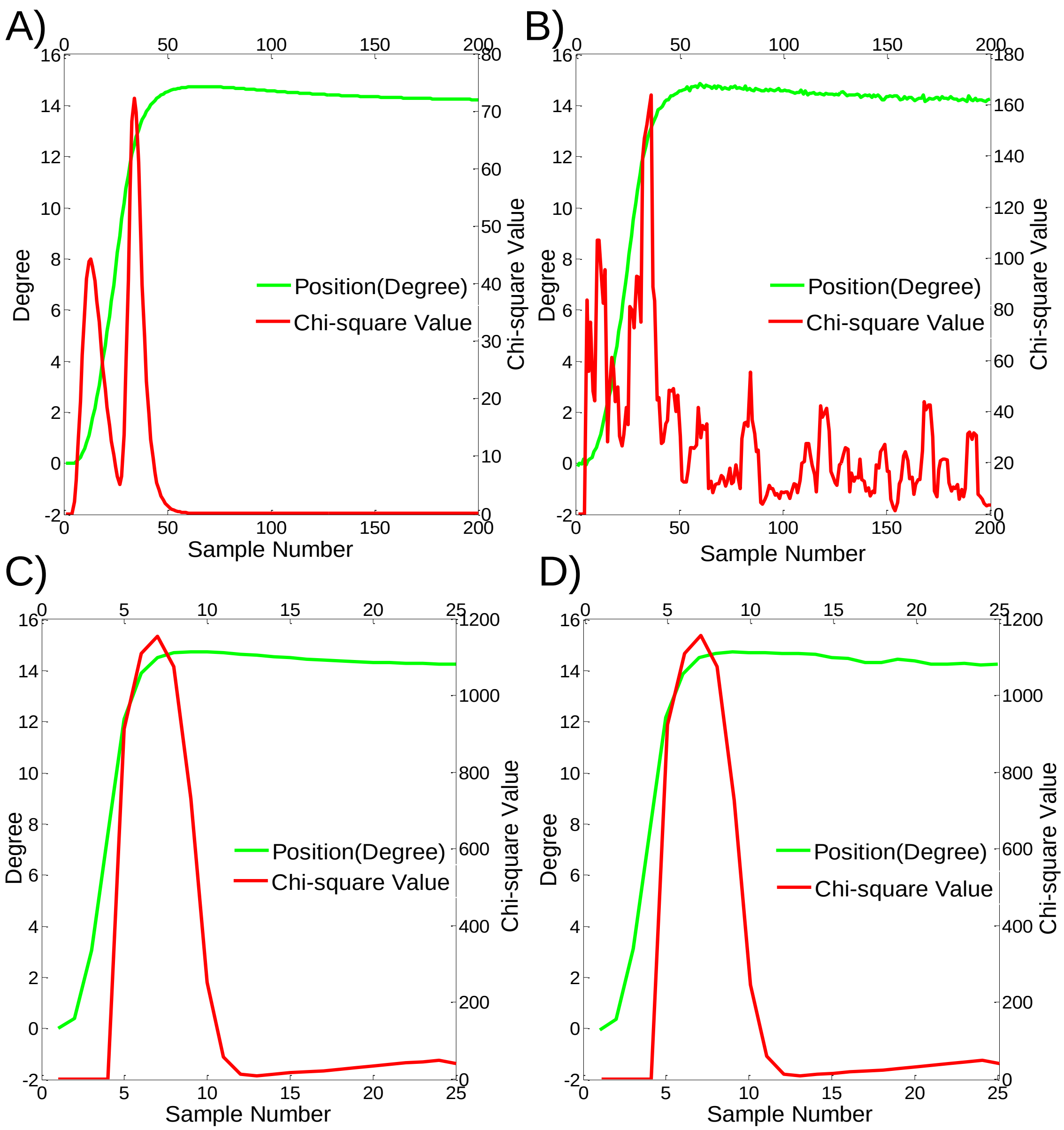

Figure 3. An Example of the Horizontal Portion of a Saccade. A) Chi-square test behavior for 1000Hz OPMM model. B) Chi-square test behavior for 1000Hz OPMM model with white noise. C) Chi-square test behavior for 120Hz OPMM model. D) Chi-square test behavior for 120Hz OPMM model with white noise.

CHAPTER III

PRACTICAL EVALUATION: IS SELECTION

Theoretical evaluation provides an estimate of the expected performance of the IS, but it is important to evaluate the IS performance in terms of the practical application. Multi Directional Fitts' Law Test and an eye-gaze-driven game Balura were employed to test the performance of the IS target selection method.

2D Fitt's Law Test

The 2D Fitt's Law discrete task measures a performance of a target selection scheme via a throughput calculation discussed in the detail later in this subsection. The goal of the test is to select a sequence of targets presented at the various eccentricities from the center of the screen initialing each subsequent selection from the screen's center. Figure 4 illustrates an example of target selection with 2D Fitt's Law task. Commonly, the width of the target is varied, but the latest research suggests that a more accurate performance can be achieved if the target width is fixed and only distance to the target is varied (Guiard, 2009). General implementation guidelines for the 2D Fitt's Law discrete task, presented by Zhang and MacKenzie (2007) were followed with real-time eye movement identification protocol designed by Koh and colleagues (Koh, et al. 2010).

The experiment, involving 2D Fitt's Law discrete task test was conducted with three levels of target distance. Each trial started with an initial target appearing at the center of the screen. As soon as the initial target was selected (the initial selection was always done by the DT method) a target appeared on the screen at a new location and the timer for the selection completion time was initiated. Subject's goal was to select this target as soon as possible. The target was available for the selection until it was successfully selected, i.e., sometimes a subject had to make several selection attempts before the target was successfully selected. If subjects selected the target, the initial target appeared again. This sequence was repeated until subjects successfully selected 8 targets for each target distance level. The radius of the target was fixed to approximately 1.52° of the visual angle (64pixels). Three eccentricity levels were approximately 7.14°, 8.93°, and 10.71° (300, 375, and 450pixels). Each eccentricity levels consisted of 16 possible selections. Once the coordinates of the first selection point by each selection scheme were recorded, the trial ended and the duration for the target selection completion time was recorded. In order to avoid a learning effect, the order of the selection schemes was randomly selected.

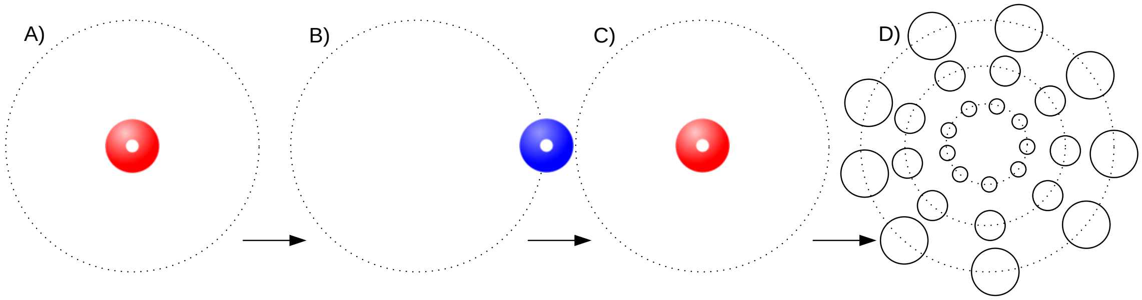

Figure 4. 2D Fitt's Law Discrete Task. A) central target appears to initiate target selection task B) Peripheral target appears after the central target is selected with DT method C) new central target represents the start of the new trial.

Target Selection Performance Evaluation Test

2D Fitt's Law discrete task provides a good test bed for testing a performance of any target selection scheme. The most common evaluation measures for any target selection method are speed, accuracy, and throughput (Douglas et al., 1999). In this paper, speed is equivalent to target selection time. Accuracy is usually reported as an error rate – the percentage of selections outside the target. These measures are typically analyzed over a variety of tasks. Throughput, measured in bits per second, is a composite measure derived from both the speed and accuracy of the selections make as a result of an interaction scheme. Equation (11) explains Throughput calculation for the successful target selection.

$$\mathrm{Throughput} = \frac{\mathrm{ID_e}}{\mathrm{CT}} \tag{11}$$

where CT is the completion time of the successful selection of a target.

Equation (12) calculates the effective index of difficulty.

$$\mathrm{ID_e} = \log_2\left(\frac{\mathrm{D}}{\mathrm{W_e}} + 1\right) \tag{12}$$

the term $\mathrm{ID_e}$ is the effective index of difficulty that is measured in “bits.” It is calculated from D, the distance to the target, and $\mathrm{W_e}$ the effective width of the target. The concept of the “effective” width ($\mathrm{W_e}$) is critical since $\mathrm{W_e}$ is the width of the distribution of selection coordinates computed over a sequence of trials which can be obtained by the equation in (13).

$$\mathrm{W_e} = 4.133 \cdot \mathrm{SD_x} \tag{13}$$

In equation (13), SDx is the standard deviation of the differences between selection and the center of the target coordinates that is measured along the axis of approach to the target. This implies that W_e reflects the spatial variability or accuracy in the sequence of trials. Therefore, throughput captures both the speed and accuracy of the user performance.

Balura Game

Balura is a real-time eye-gaze guided video game. In other words, Balura is the game that simulates real time gaming environment such as massive battle grounds in World of Warcraft game. There are 40 balloons which moves randomly at the same time in Balura and 20 of them are red and the others are blue. Blue balloons are considered as same team, but red ones are considered as opponent. The main objective of Balura is to pop all red balloons as soon as possible with different selection methods. In order to provide a visual feedback to the player, the border of blue balloons will grow when the player dwells on them. Nothing will happen for red balloons. Figure 5 shows an example of a blue balloon and visual feedback.

There are four mode in Balura based on balloons' movement type. In the first Balura mode, each balloon does not bounce each other. But when the balloon hits the well, it bounces off. Visually, blue balloons are on top of red balloons. Every balloon has same speed. The second Balura mode has same constraints as the first mode except every balloon will have randomly generated velocity after they hit the wall. The third Balura mode is the same as second mode plus randomly generated velocity and direction after balloons hit the wall. In the fourth Balura mode, balloons occasionally stops and they starts moving with randomly generate velocity and direction. Of course, the fourth Balura mode contains all the property of the third Balura mode. In our experiment, only the fourth Balura mode was selected to test since the fourth Balura mode is the mode that has highest possibility of saccade movements.

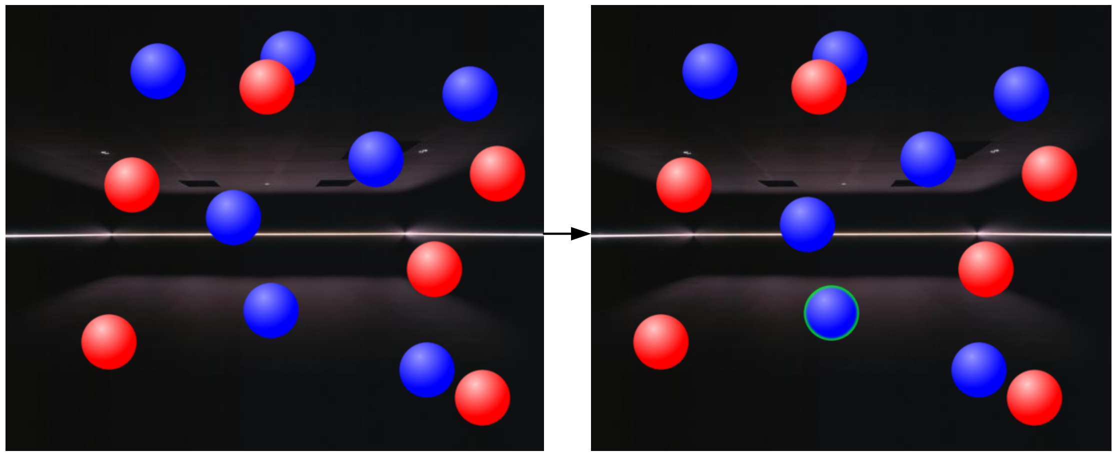

Figure 5. An Example of Visual Feedback for Blue Balloons.

CHAPTER IV

METHODOLOGY

Real Time Testing Procedure of the Proposed Interaction Models

The real time performance test of proposed interaction schemes were designed to have three phases. At first, an accuracy test was conducted and it measures individual accuracy and data loss. Then, 2-D Fitts' Law test was performed to evaluate the performance of selection models. Finally, Balura will be played.

Participants

A total of 31 participants volunteered to evaluate the performance of our selection schemes. Participants' ages were from 19 to 45 (mean = 25). None of the participants had prior experience with eye tracking. Among these participants, 15 had normal vision and 16 wore glasses or contacts. Two subjects had an abnormal vision attributed to astigmatism. Based on the result of the accuracy test, only 14 recordings were analyzed and discussed.

Apparatus

The experiments were conducted with Tobii x120 eye tracker, which is represented by a standalone unit connected to a 19inch flat panel screen with resolution of 1280x1024. The eye tracker performs binocular tracking with the following characteristics: accuracy 0.5°, spatial resolution 0.2°, drift 0.3° with eye position sampling frequency of 120Hz. The Tobii x120 model allows 300x220x300 mm freedom of head movement. Nevertheless, a chin rest was employed for higher accuracy and stability.

Accuracy Test

This procedure involves participants looking at 17 sequentially presented points that are uniformly distributed on the computer screen. When a subject fixates at each point, the raw eye position signal is processed by Identification by a Kalman Filter and corresponding fixation parameters such as location coordinates, the onset time, and the duration are determined. The coordinates of the eye position within the detected fixations are compared to the center of presented stimulus. This allows for the computation of error between reported location of the gaze and the actual gaze point. At the end of the recording, the error values are averaged between all points and presented on the computer screen. Additionally, an accuracy test computes and presents a data loss parameter that indicates the amount of erroneous (not detected) eye position samples provided by an eye tracker for the participant. If a subject had the pointing error is greater than 2° or the data loss is greater than 20%, he or she could not be able to take further testing procedures.

17 subjects' recording was discarded if those data had an average measured error greater than 2° or data loss greater than 20%. The average accuracy for the remaining fourteen subjects was 1.14° (SD=0.44) and the average data loss was 13.70% (SD=13.09). One subject was not able to finish multi directional Fitts' Law task since the validity result was lower than 80%.

Evaluation Metrics

Root mean square error (RMSE) was employed to assess the accuracy of saccades' offset (ending point) coordinates prediction.

For 2D case, RMSE can be calculated by the equation (14).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \sqrt{(x_i - \bar{x}_i)^2 + (y_i - \bar{y}_i)^2}}{n}} \tag{14}$$

In equation (14), x_i and y_i are the actual saccade offset position. $\bar{x}_i$ and $\bar{y}_i$ are the predicted saccade offset positions by saccade trajectory prediction model.

CHAPTER V

RESULTS

Time Savings

Most Ideal Case

Considering equation (9), and that the prediction about saccade's amplitude can be done at the first millisecond of its trajectory (k=1 in the equation (5)). We can deduct that the amount of time saved by IS interaction is 37.98% for very close targets and 50.49% for the targets which are 40° away from user's current location. IS provides 10.3-34.31% selection time reduction for the saccades of the same amplitude range when compared to SO scheme. When SO selection scheme is compared to the DT selection in the same amplitude range, 30.85% selection time reduced for 1° saccades and 24.63% the 40° saccade. Both SO and DT are sampling frequency independent, therefore same trend remains for any sampling frequency.

Saccade's Trajectory Simulated by 2D-OP at 1000Hz

In 1000Hz Saccade trajectory regression model, saccade amplitude prediction can be done at the 9-13ms. We can deduct that the amount of time saved by the IS interaction is 38.29% for very close targets and 47.53% for the targets which are 40° away from user's current location. The IS provides 5.44-30.75% selection time reduction if compared to SO selection for the same saccade amplitude range.

Saccade's Trajectory Simulated by 2D-OP at 120Hz

In 120Hz Saccade trajectory regression model, saccade amplitude prediction can be done at the 48-64ms. We can deduct that the amount of time saved by the IS interaction is 20.29% for very close targets and 36.37% for the targets which are 40° away from user's current location. The IS provides time saving starting with saccade amplitude of 18°, resulting in 0.56% selection time reduction at this amplitude. This number is increased to 15.58% at the saccade amplitude of 40°.

Accuracy of Saccade's Prediction

Table 1 shows the saccade's amplitude prediction accuracy for the saccadic trajectory simulated by the 2D-OP model at 1000Hz and the amplitude predicted based on the equation (9).

It is possible to see that accuracy of prediction is reduced, due to the added noise. Equation (9) employed with saccade's trajectory simulated at 120H creates extremely large errors, therefore supporting the argument for creating a separate amplitude prediction equation for the lower sampling case.

Table 1.Saccade's Trajectory Prediction Errors, Saccades Are Simulated at 1000Hz	
Sampling frequency, noise condition	RMSE (SD)
1000Hz, no noise	1.97° (1.52°)
1000Hz, white noise added	3.61° (2.89°)

Table 2 presents the saccade's amplitude prediction accuracy for the saccadic trajectory simulated by the 2D-OP model at 120Hz and the amplitude predicted based on the equation (10).

In cases with no noise 1000Hz data allowed for more accuracy in terms of prediction of saccade's offset coordinates. However, it is possible to see that the errors for the 120Hz case are lower than for the 1000Hz case, in the situation when the noise was added, but in 120Hz case the peak occurs later than in the 1000Hz during the saccade, therefore providing less time savings. The difference between 120Hz case with no noise and the noise added is very small indicating that the same magnitude of distortion provides lower impact in terms of the accuracy reduction in the lower frequency case.

Table 2. Saccade’s Trajectory Prediction Errors, Saccades Are Simulated at 120Hz.	
Sampling frequency, noise condition	RMSE (SD)
120Hz, no noise	2.39° (1.72°)
120Hz, white noise added	2.53° (1.9°)

Noise Reduction Algorithm for Practical Evaluation

Since the root mean square error of saccade trajectory prediction with white noise is greater than saccade trajectory prediction error without noise, noise reduction algorithm is applied to real time eye tracking for practical evaluation. Linear smoothing filter with weighted average is deployed to reduce the noise. Equation (15) shows the weighted average equation for noise reduction. Linear smoothing filter averages the measured position, its previous position, and its predicted position from the Kalman filter.

$$\bar{x} = \frac{\dot{x}_{i-1} + \dot{x}_i + \hat{x}_i^-}{3} \qquad (15)$$

In equation (15), $\dot{x}_i$ is the current measured position, $\dot{x}_{i-1}$ is its previous position, and $\hat{x}_i^-$ is predicted position by the Kalman filter.

Practical Evaluation

Due to the fact that we have employed the eye tracking hardware with the sampling frequency of 120Hz, and the fact that 120Hz model provides better accuracy with noise, we have employed the equation (10) for the saccade's amplitude prediction with saccade's direction prediction conducted by the formula (8) OPMM data and our hardware constraint for the eye tracker was 120Hz, we decided to use 120Hz saccade trajectory prediction model as a basis for practical implementation of the Instantaneous Saccade selection scheme.

Multi Directional Fitt's Law Test

Throughput

Figure 6 shows the performance of four selection schemes in terms of throughput. In the short target distance level, DT selection scheme provided an average throughput for target selection of 2.33bps (SD=1.21). The IS selection provided an average throughput of 2.50bps (SD=1.38) which is approximately 7% higher than DT selection. The HS selection provided an average throughput of 3.56bps (SD=1.10) which is approximately 42% higher than IS selection. The SO selection scheme provided an average Throughput of 4.09bps (SD=1.39), and it was approximately 15% higher than HS selection. The difference in throughput was statistically significant, $F(3,36)=9.56$, $p<0.0001$.

In the medium target distance level, the DT selection scheme provided an average throughput for target selection of 2.31bps (SD=1.23). The IS selection provided an average throughput of 2.42bps (SD=1.11) which is approximately 5% higher than DT selection. The HS selection provided an average throughput of 3.40bps (SD=1.08) which is approximately 40% higher than IS selection. The SO selection scheme provided an average Throughput of 4.15bps (SD=1.03), and it was approximately 22% higher than HS selection. The difference in throughput was statistically significant, $F(3,36)=9.89$, $p<0.0001$.

In the long target distance level, the DT selection scheme provided an average throughput for target selection of 1.94bps (SD=0.84). The IS selection provided an average throughput of 2.18bps (SD=0.69) which is approximately 12% higher than DT selection. The HS selection provided an average throughput of 3.24bps (SD=1.08) which is 49% higher than IS selection. The SO selection scheme provided an average Throughput of 4.50bps (SD=1.80), and it was about 39% higher than HS selection. The difference in throughput was statistically significant, $F(3,36)=19.57$, $p<0.0001$.

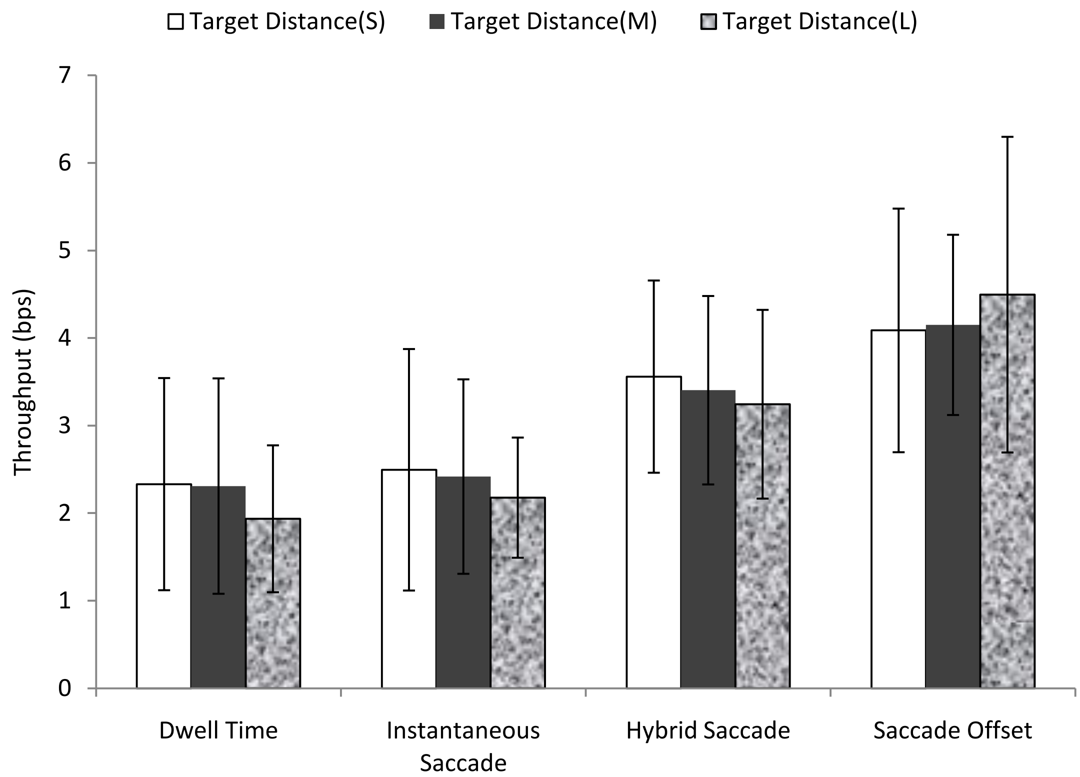

Figure 6. Throughput as a Function of Interaction Scheme.

Completion Time

Figure 7 represents average completion time of the target selection task. In the short target distance level, average completion time for the successful target selection in terms of the DT selection was 23.40s (SD=20.67). Average completion time for the IS selection was 14.32s (SD=5.82) which is about 61% faster than DT selection. Average completion time for the HS selection was 8.80s (SD=2.81) which is approximately 60% faster than IS selection. The completion time of HS selection is also approximately 1% faster than SO selection. Average completion time for the SO selection was 8.87s (SD=4.70). The difference in completion time was statistically significant, $F(3,36)=5.78$, $p<0.0025$.

In the medium target distance level, average completion time for the successful target selection in terms of the DT selection was 23.42s (SD=17.03). Average completion time for the IS selection was 17.06s (SD=8.34) which is about 37% faster than DT selection. Average completion time for the HS selection was 10.50s (SD=2.89) which is approximately 62% faster than IS selection. Average completion time for the SO selection was 9.13s (SD=2.94) which is approximately 15% faster than HS selection. The difference in completion time was statistically significant, $F(3,36)=6.57$, $p<0.0012$.

In the long target distance level, average completion time for the successful target selection in terms of the DT selection was 26.51s (SD=15.53). Average completion time for the IS selection was 17.19s (SD=5.78) which is about 35% faster that DT selection. Average completion time for the HS selection was 11.99s (SD=3.46) which is approximately 30% faster than IS selection. Average completion time for the SO selection was 10.66ms (SD=8.14) which is approximately 11% faster than HS selection. The difference in completion time was statistically significant, $F(3,36)=8.91$, $p<0.0002$.

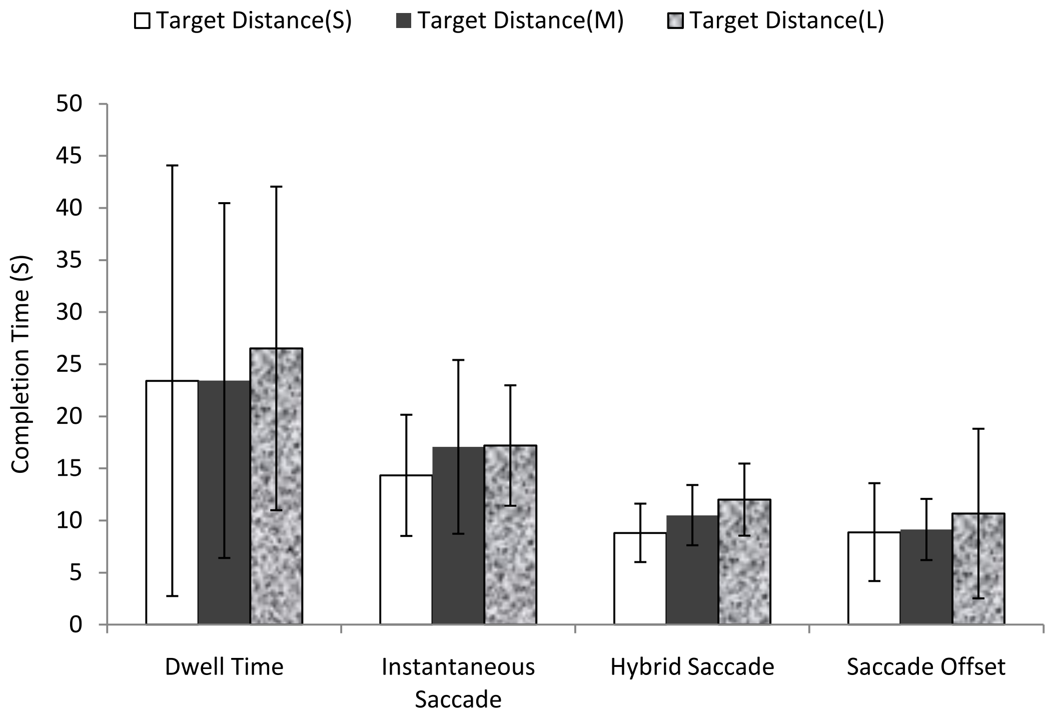

Figure 7. Completion Time As A Function Of Interaction Scheme.

Error Rate

The error rate is calculated by dividing the total number of selections into the number of unsuccessful selections in percentage. In the short target distance level, average error rate for the successful target selection in terms of the DT selection was 6.08% (SD=7.60) which is about 90% lower than IS selection. Average error rate for the IS selection was 59.16% (SD=12.91) which is approximately 5% lower than HS selection. Average error rate for the HS selection was 62.39% (SD=13.87). Average error rate for the SO selection was 53.59% (SD=18.63) which is approximately 14% lower than HS selection. The difference in completion time was statistically significant, $F(3,36)=81.96$, $p<0.0001$.

In the medium target distance level, average error rate for the successful target selection in terms of the DT selection was 10.62% (SD=12.2) which is approximately 85% lower than IS selection. Average error rate for the IS selection was 69.19% (SD=13.38). Average error rate for the HS selection was 65.27% (SD=12.82) which is approximately 6% lower than IS selection. Average error rate for the SO selection was 53.01% (SD=20.10) which is approximately 19% lower than HS selection. The difference in completion time was statistically significant, $F(3,36)=65.25$, $p<0.0001$.

In the long target distance level, average error rate for the successful target selection in terms of the DT selection was 14.44% (SD=10.84) which is approximately 79% lower than IS selection. Average error rate for the IS selection was 67.63% (SD=11.09). Average error rate for the HS selection was 66.79% (SD=11.24) which is approximately 1% lower than IS selection. Average error rate for the SO selection was 56.33% (SD=18.73) which is approximately 16% lower than HS selection. The difference in completion time was statistically significant, $F(3,36)=66.18$, $p<0.0001$. Figure 8 presents the error rate in multi directional Fitts' Law task.

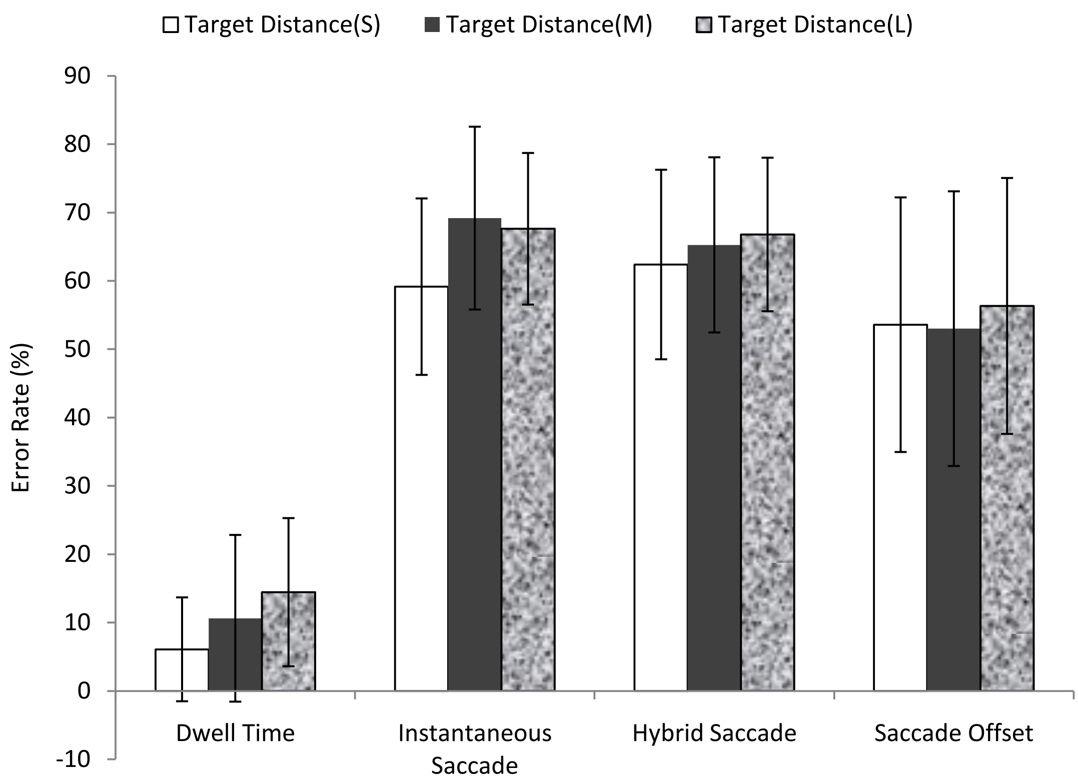

Figure 8. Error Rate as a Function of Interaction Scheme.

Balura Game

In order to compare the performance of Balura for different interaction scheme, the completion time and the error rate is analyzed. The completion time for the Balura is the time to pop all red balloons. The error rate for the Balura is calculated by the same way we did for multi directional Fitts' Law test.

The average completion time of the DT selection was 54.21s (SD=50.67). Average completion time for the IS selection was 15.31s (SD=7.82) which is approximately 72% faster than DT selection. Average completion time for the HS selection was 13.71s (SD=6.49) which is about 10% faster than IS selection. Average completion time for the SO selection was 13.31s (SD=6.98) which is about 3% faster than HS selection. The difference in completion time was statistically significant, $F(3,39)=10.81$, $p<0.0001$.

The average error rate for the successful target selection in terms of the DT selection was 20.10% (SD=11.94) which is approximately 64% lower than IS selection. Average error rate for the IS selection was 56.08% (SD=12.37) which is about 5% lower than HS selection. Average error rate for the HS selection was 59.27% (SD=13.97). Average error rate for the SO selection was 56.55% (SD=10.48) which is approximately 5% lower than HS selection. The difference in completion time was statistically significant, $F(3,39)=50.17$, $p<0.0001$.

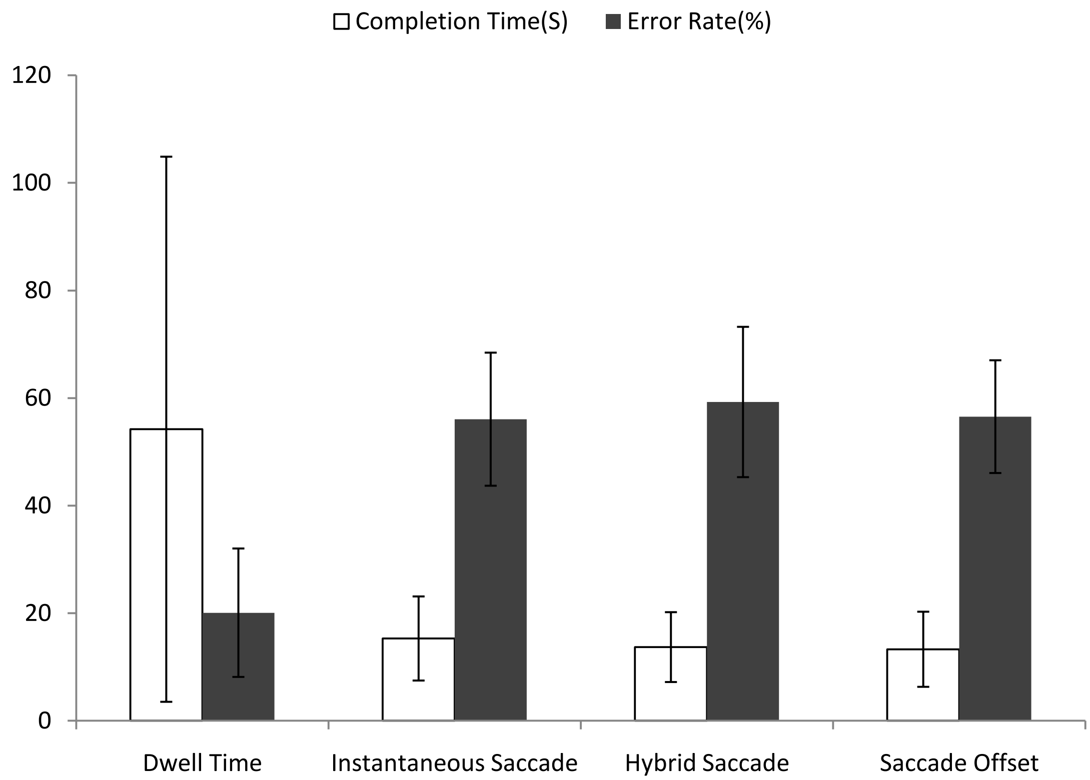

Figure 9. The Completion Time and the Error Rate of Balura.

Balura Result for Saccades of Greater than 18°

In the theoretical evaluation for 120Hz sampling frequency, the result represented that the completion time for IS was faster than SO when the saccade amplitude is more than 18°. Therefore, the completion time graph for saccade selection with the amplitude of more than 18° is represented in Figure 10. The average completion time of the DT selection was 1.92s (SD=1.72). Average completion time for the IS selection was 0.10s (SD=0.01) which is approximately 95% faster than DT selection. Average completion time for the HS selection was 1.18s (SD=1.02) which is about 90% slower than IS selection. Average completion time for the SO selection was 0.76s (SD=0.16). The IS selection provided 87% than SO selection for the target distance with more than 18°. The difference in completion time was not statistically significant and the sample size for each selection scheme is relatively small, $F(3,12)=2.68$, $p<0.094$.

In terms of the error rate, the error rate for DT selection was 27.27%. The error rate for HS selection was 66.67% and 42.86% for SO selection. Unfortunately, there was no succcced IS selection for target amplitude of more than 18°.

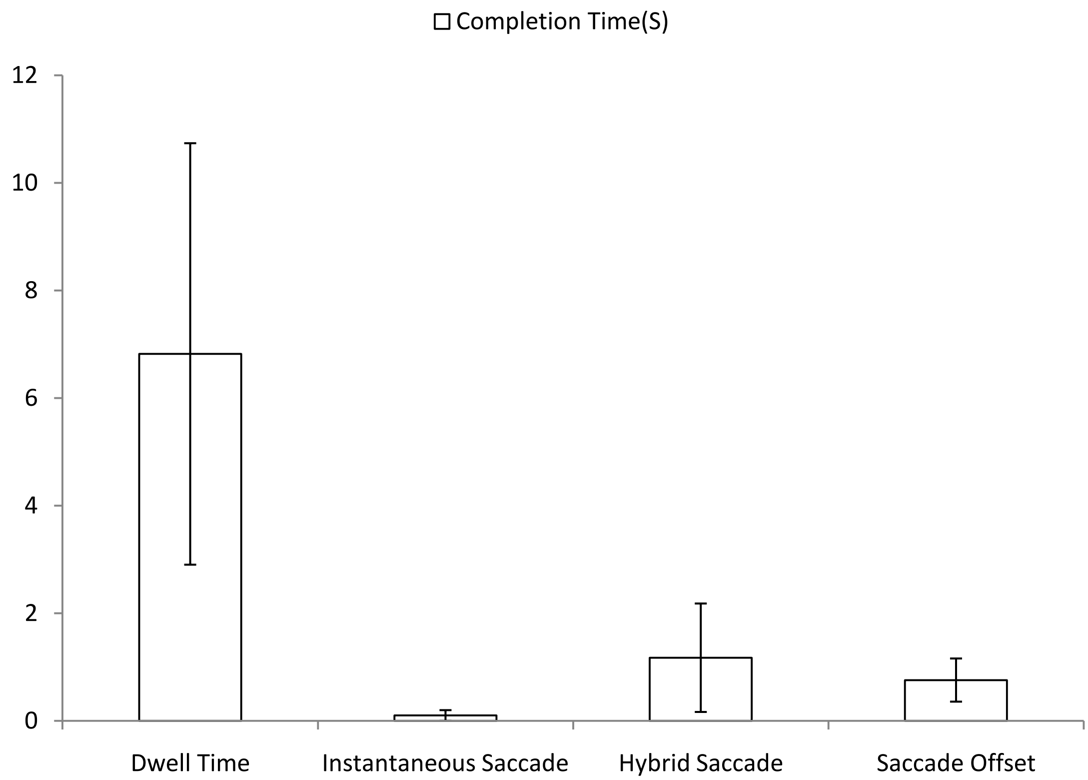

Figure 10. The Completion Time for the Target Amplitude of More Than 18°.

Completion Time vs. Index of Difficulty

Relation of completion time to the index of task difficulty was investigated to find how the required movement characteristics effect the completion time.

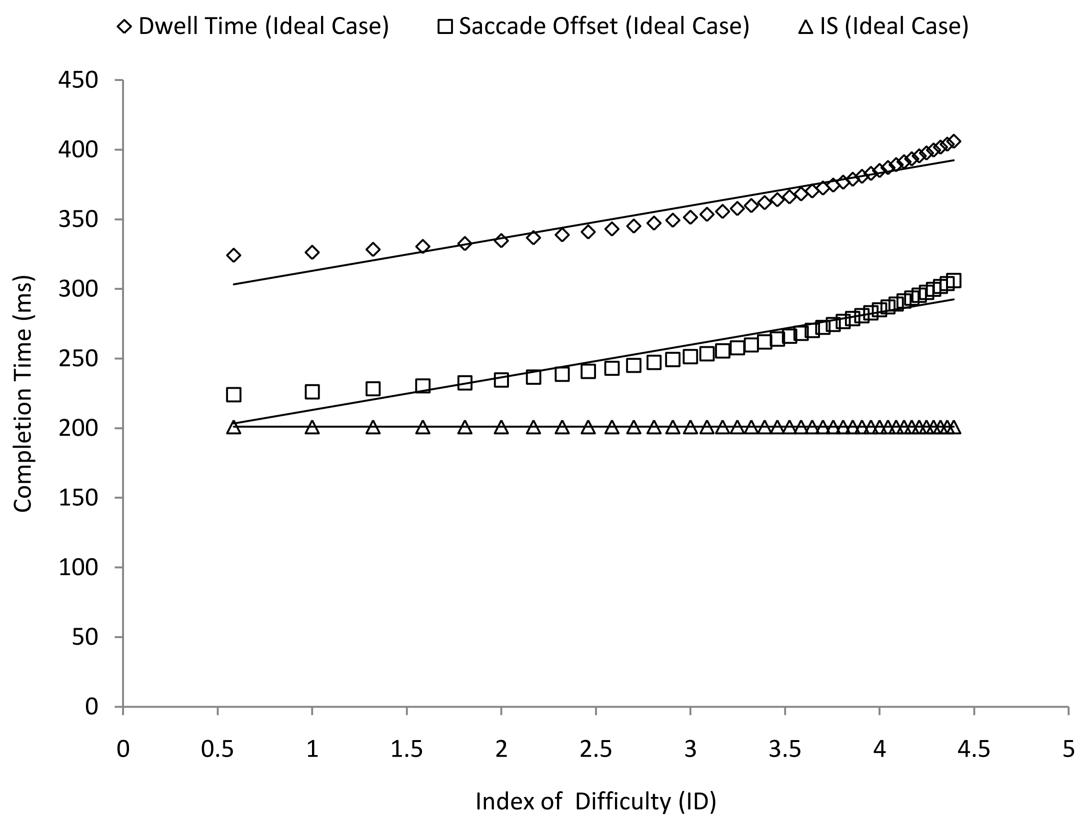

Figure 11, Figure 12, and Figure 13 illustrate the regression equations for prediction the completion time on the basis of knowledge of required movement amplitude in theoretical evaluation. These seven equations are:

Dwell Time Selection

$$CT = 23.39 * ID + 289.7 \ (R^2 = 0.9014) \tag{16}$$

Saccade Offset Selection

$$CT = 23.39 * ID + 189.7 \ (R^2 = 0.9014) \tag{17}$$

Instantaneous Saccade Selection (Ideal Case)

$$\mathrm{CT} = -2.134 * 10^{-14} * \mathrm{ID} + 201 \ (\mathrm{R}^2 = \mathrm{N/A}) \quad (18)$$

Instantaneous Saccade Selection (1000Hz)

$$\mathrm{CT} = 1.179 * \mathrm{ID} + 208.4 \ (\mathrm{R}^2 = 0.8909) \quad (19)$$

Instantaneous Saccade Selection (1000Hz with white noise added)

$$\mathrm{CT} = 0.2379 * \mathrm{ID} + 205.5 \ (\mathrm{R}^2 = 0.5104) \quad (20)$$

Instantaneous Saccade Selection (120Hz)

$$\mathrm{CT} = 3.782 * \mathrm{ID} + 245.7 \ (\mathrm{R}^2 = 0.6706) \quad (21)$$

Instantaneous Saccade Selection (120Hz with white noise added)

$$\mathrm{CT} = 4.573 * \mathrm{ID} + 244 \ (\mathrm{R}^2 = 0.8453) \quad (22)$$

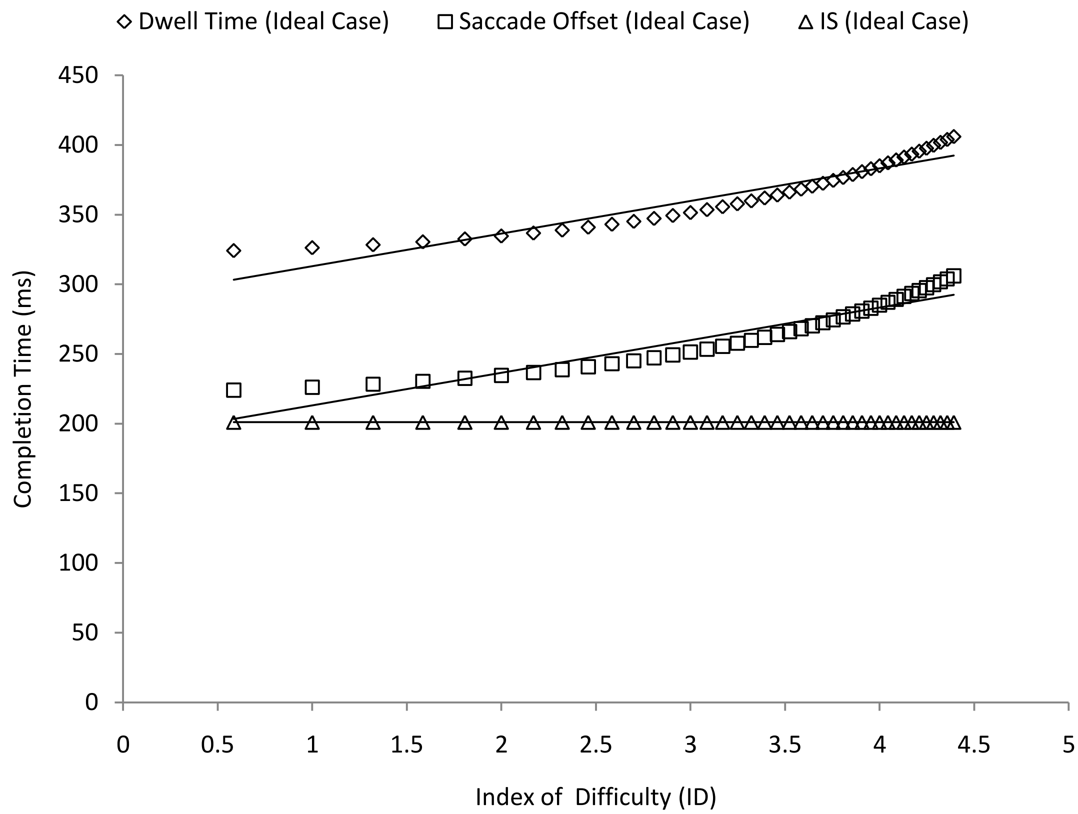

Figure 11. Relation of Completion Time to the Index of Task Difficulty for DW, SO, and IS selection (Ideal Case).

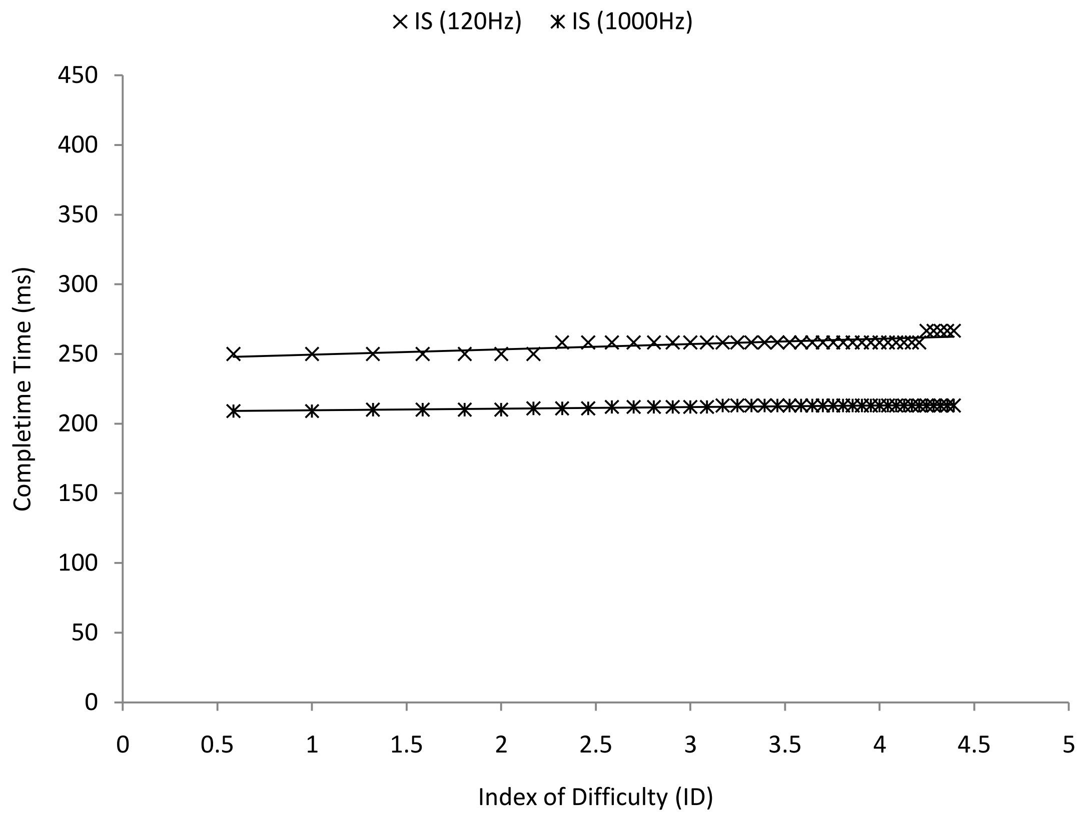

Figure 12. Relation of Completion Time to The Index Of Task Difficulty for IS (1000Hz) and IS (120Hz).

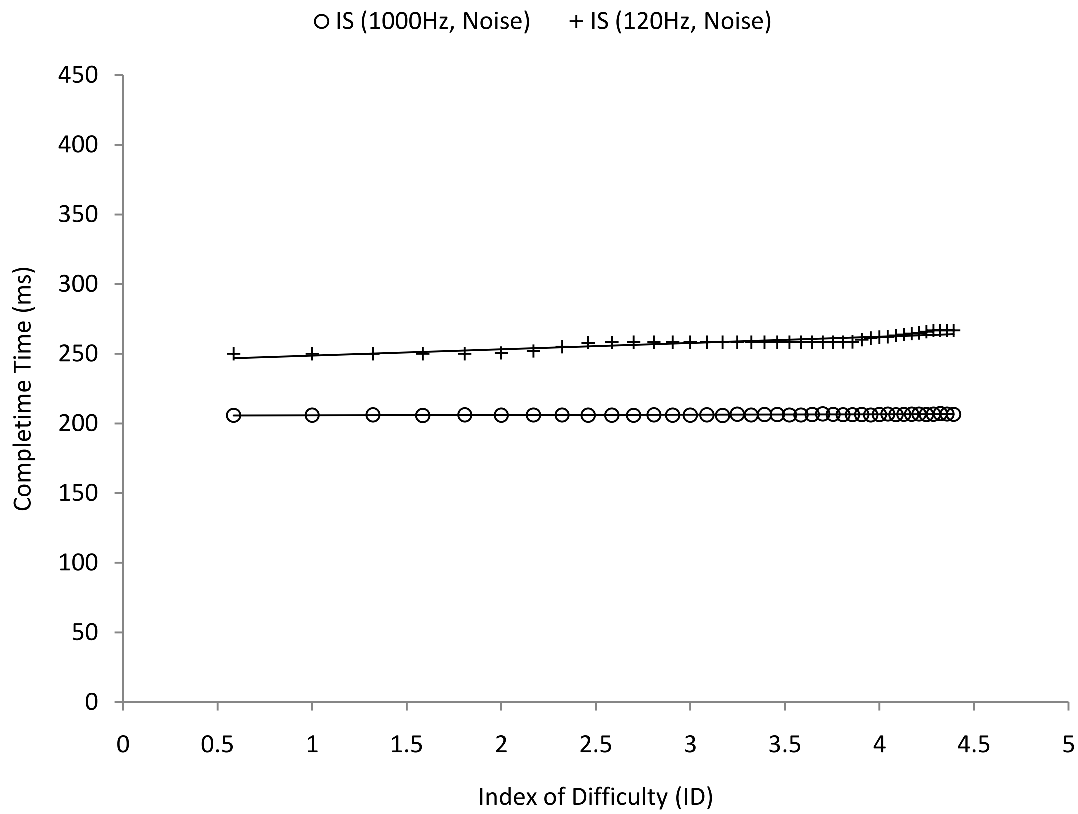

Figure 13. Relation of Completion Time to the Index of Task Difficulty for IS (1000Hz with white noise) and IS (120Hz with white noise).

Figure 14 presents the regression equations for prediction of the completion time in the multi directional Fitts' Law test. The four regression equations are:

Dwell Time Selection

$$\mathrm{CT} = 435.6 * \mathrm{ID} + 672.3\ (\mathrm{R}^2 = 0.005131) \quad (23)$$

Instantaneous Saccade Selection

$$\mathrm{CT} = 768.54 * \mathrm{ID} - 497.32\ (\mathrm{R}^2 = 0.1082) \quad (24)$$

Hybrid Saccade Selection

$$\mathrm{CT} = 349.76 * \mathrm{ID} - 34.633\ (\mathrm{R}^2 = 0.0947) \quad (25)$$

Saccade Offset Selection (1000Hz)

$$\mathrm{CT} = 463.9 * \mathrm{ID} - 313.9\ (\mathrm{R}^2 = 0.0568) \quad (26)$$

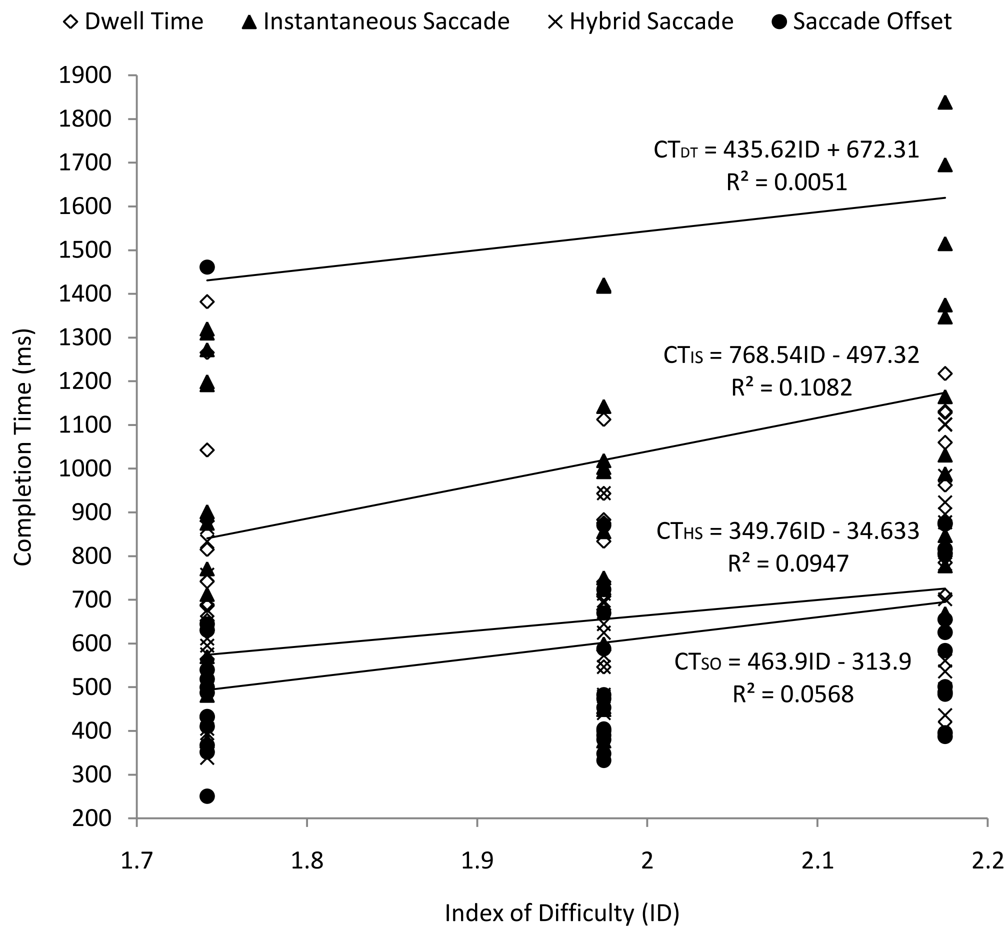

Figure 14. Relation of Completion Time to the Index of Task Difficulty for DW, IS, HS, and SO Selection Schemes in Multi Directional Fitts' Law Task.

In theoretical evaluation results, index of task difficulty in Dwell Time and Saccade Offset selection highly effects the completion time. On the contrary, the completion time of the ideal Instantaneous Saccade selection is almost constant with any index of task difficulty. The index of task difficulty in the IS selection with 1000Hz and 120Hz are also less effective on the completion time even with white noise.

In the multi directional Fitts' Law test result, it looks that predicting the completion time by the index of difficulty is not easy since the regression equations are not robust. In other words, the completion time and the index of task difficult are much more independent from each other when compared to the theoretical evaluation result.

CHAPTER VI

DISCUSSION

Difficulties in the Saccade Trajectory Prediction Model

Based on our observations, participants were able to complete the task faster when Instantaneous Saccade (IS) selection was applied. This result is remarkable even though the IS selection has the highest error rate the initial selection. This result seems peculiar but if we consider the nature of the Human Visual System (HVS) we can find the explanation for this phenomenon. Saccade movements in the HVS are not always precise and are subject to frequent undershoots or overshoots (Leigh & Zee, 2006). Such HVS behavior naturally decreases the accuracy of target selection. Nevertheless, such errors do not negate the advantage of the IS interaction method which, in terms of the completion time, is almost two times smaller than DT selection.

Practical implementation of the IS selection involves some technical difficulties. High error rate is the one of those difficulties. The IS selection occurs only when saccade movement is detected by Kalman Filter using a Chi-square test threshold. Since the saccade movement is the most rapid eye movement in the HVS and has very short duration, few eye position samples are available to determine the first peak in the Chi-square test (we are using a 120Hz sampling frequency of the eye tracker). Specifically, there are approximately 2.90 eye position samples for making a saccade trajectory prediction in small target distance selection (SD=1.03). Sometimes the peak in the Chi-square test signal is not correctly identified and the initial target selection attempt does not succeed. The average number of attempts was 3.84 for medium target distance selection (SD=2.19), and the average number of attempts was 3.46 for long target distance selection (SD=1.31). Thus, for the future work, we plan to improve the Instantaneous Saccade selections by incorporating more robust peak detection methods.

When saccade detection fails, e.g. due to noise, IS selection is delayed even if the eye correctly lands on the target location. In cases like this the system will wait until the user's eye makes an additional detectable saccade which triggers the selection. In rare cases like this the DT scheme is superior to the IS method. This fact might be the one of the reason that IS had higher error rate than DT.

We found that the number of the unique signature of Chi-square test behavior for single saccade was decreased during the practical evaluation. Having the certain Chi-square test pattern in saccade is important for saccade trajectory model, especially for saccade onset prediction. In theoretical evaluation, every simulated saccade had same Chi-square test signature which has 2peaks in 1000Hz condition. Also, every simulated saccade had same Chi-square test behavior which has 1peak for 120Hz. However, there were only 16.92% of detected saccades had 1peak and 19.62% of detected saccades had 2peaks in practical evaluation with 120Hz sampling frequency. This fact is one of the challenges in the saccade trajectory prediction and it may be caused by the imperfection of the HVS or the system noise.

Direction prediction was another difficulty in the saccade trajectory prediction. For the perfect direction prediction of a saccade, the onset position of the saccade and the offset position of the saccade are needed. However, direction prediction model uses only the onset position of the saccade and the next position which caused high RMSE. Thus, we plan to improve direction prediction model for the future.

Application for IS Interaction

In its current state, Instantaneous Saccade-based interaction will be favorable to gaming applications. In this mode of interaction, accuracy is less important than targeting speed. In the action oriented game World of Warcraft (2009), players compete in battlegrounds – places where a team of players must overpower the opposite team to complete a task. The interaction between players occurs extremely fast with a player targeting an enemy player and then casting an instantaneous damaging spell. The speed of an enemy player's selection eventually translates into a victory or a loss. In this type of interaction even a saved fraction of a second is a significant achievement. In World of Warcraft, it is impossible to select or damage a friendly player, therefore there is no penalty if instantaneous selection misses the target. To alleviate the impact of misses, the IS selection can be run in parallel with a DT selection scheme allowing the user to perform successful selection in cases when saccade amplitude prediction misses the target.

We are aware of the fact that during the interaction task each subject was presented only with one target for selection at a time. This paper specifically explored potential benefits that can be gained as a result of a new interaction method. The tasks that have multiple target choices for selection will be a part of our future work.

CHAPTER VII

CONCLUSION

In this paper, we presented an Instantaneous Saccade (IS) selection method that allows target selection at the beginning of the eye movement (saccade) that moves the eye to the target. The new IS method was compared to the conventional Dwell Time (DT) selection method with dwell time duration of 100ms, Hybrid Saccade (HS) selection which combines DT selection and IS selection, and the Saccade Offset (SO) selection method (essentially a DT selection method without the dwell time threshold). Each method was evaluated through a series of target selection tasks where the completion time of an individual task and the completion time of a series of tasks were recorded. In addition, each selection method was evaluated by calculating pointing device (eye tracker) throughput when driven by each of the presented selection schemes. The results indicate that IS selection is 72% faster than DT selection, and 15% slower than SO selection. In addition, IS selection provided 87% faster than SO selection for the target distance with more than 18°. In terms of the sequence of targets selection task the IS method is 44% faster than DT and 69% slower than SO. The IS method provides approximately 8% increased throughput (2.37bps vs. 2.19bps) when compared to the DT method. The throughput achieved by the IS method is approximately 79% lower than the SO method.

While providing a significant increase in completion time and throughput, the IS selection method does not address the Midas Touch problem discussed by Jacob (1990). Considering this limitation, we expect that the IS method will be beneficial in virtual environments where accidental selection is not detrimental to the user experience. More specifically we envision that the IS method is applicable in gaming environments where targeting speed is much less important than the accuracy of the initial selection.

For the future work, we will explore how the Chi-square test result behaves in detected saccades with 1000Hz sampling frequency eye tracking environment. Also, we will evaluate our selection schemes in 1000Hz sampling frequency real time eye tracking since our theoretical evaluation was originally based on 1000Hz sampling frequency. In addition, we will explore vertical and horizontal component of saccades movements separately in order to get more reliable saccade trajectory prediction model. Developing the noise reduction algorithms is also planned for the future work.

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VITA

Do Hyong Koh was born in Seoul, Republic of Korea on July 28, 1981, the son of Hungsun Koh and Yongsoon Kyung. He grew up in Cheongju, Republic of Korea, where he obtained his pre-university college degree in 2000. From 2000 to 2007, he attended Sogang University, Seoul, where he obtained the degree of Bachelor of Engineering in Computer Science. He entered The Graduate College of Texas State University-San Marcos as a full-time student in the Fall of 2007.

Permenanet Affress: Sachang-dong 270

Sila APT #2-607

Heungdeok-gu, Cheongju-si, Chungcheongbuk-do

Republic of Korea, 361833

This thesis was typed by Do Hyong Koh.