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# HUMAN PERFORMANCE MODELING FOR TWO-DIMENSIONAL DWELL-BASED EYE POINTING

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## Abstract

*Recently, Zhang et al. (2010) proposed an effective performance model for dwell-based eye pointing. However, their model was based on a specific circular target condition, without the ability to predict the performance of acquiring conventional rectangular targets. Thus, the applicability of such a model is limited. In this paper, we extend their one-dimensional model to two-dimensional (2D) target conditions. Carrying out two experiments, we have evaluated the abilities of different model candidates to find out the most appropriate one. The new index of difficulty we redefine for 2D eye pointing ( $ID_{eye}$ ) can properly reflect the asymmetrical impact of target width and height, which the later exceeds the former, and consequently the  $ID_{eye}$  model can accurately predict the performance for 2D targets. Importantly, we also find that this asymmetry still holds for varying movement directions. According to the results of our study, we provide useful implications and recommendations for gaze-based interactions.*

*Keywords: Eye pointing, Gaze input, Two-dimensional task, Human performance, Modeling.*

# 1 INTRODUCTION

In the community of human-computer interaction (HCI), researchers commonly regard quantitative performance model as a theoretical tool that can guide the development of HCI. Besides the well-known Fitts' law used for daily hand pointing task (Fitts 1954; MacKenzie 1992b; Soukoreff 2004), there have been a number of models, so far, proposed for different tasks, such as steering task (Accot 1997) and peephole pointing (Cao 2008). In recent years, a number of novel applications of gaze input, such as game control (Smith 2006) and information security (Kumar 2007), have been developed due to the advancement of eye tracking technologies. With respect to the dominant eye pointing task of gaze input, however, the suitability of Fitts' law is doubtful because of the fact that there was no consensus in different studies. In some studies (Ware 1987; Miniotas 2000; Vertegaal 2008), Fitts' law could be applied, but this is not the case in some others (Zhai 1999; Gajos 2007; Zhang 2008). These situations necessitate a new model specifically constructed for eye pointing.

Recently, Zhang et al. presented the first successful attempt for this purpose (Zhang 2010). Not using Fitts' law as the theoretical foundation to construct performance models for different tasks (Accot 1997; Cao 2008) but using a novel conception, they defined a new index of difficulty ( $ID$ ) for dwell-based eye pointing. The corresponding model can be expressed as follows:

$$T = a + b \times ID_{eye} = a + b \times \frac{e^{\lambda A}}{W - \mu} \quad (1)$$

where the symbols  $\lambda$  and  $\mu$  are two empirical constants that reflect the inherent features of eye movements, and  $a$  and  $b$  are two regression coefficients.  $A$  and  $W$  denote movement distance and target size (diameter), respectively. The fraction term is the index of difficulty of eye pointing task ( $ID_{eye}$ ). Zhang et al. carefully verified this model in different situations, justifying its reliability and advantages compared with Fitts' law and other existing models. However, they had not yet carefully confirmed this model's validity for general two-dimensional (2D) targets. The targets used in their experiments were a special case of 2D targets, i.e. circles, without considering the potential effects of target shape. Thus, the effectiveness of this model is still limited in practice. The targets, such as buttons, icons and tool bars, in conventional user interface have two properties, the width ( $W$ ) and the height ( $H$ ). This situation motivated HCI researchers to extend the one-dimensional Fitts' law model to explain 2D hand pointing (MacKenzie 1992a; Accot 2003; Grossman 2005; Yang 2010).

For eye pointing, the similar efforts are also necessary and valuable. In this paper, therefore, we extend Zhang et al.'s work to clarify the effects of both factors  $W$  and  $H$  on dwell-based eye pointing, and we also take account of the factor of eye movement direction ( $\theta$ ) that can affect the human performance in dwell-based eye pointing. The term “dwell-based” refers to the mechanism of command activations. In gaze-based interactive systems, when the eye cursor is continuously dwelling in the area of the target up to a given time threshold, the corresponding command will be activated. This is a simple but effective solution to overcome the “Midas-Touch” problem (Jacob 1990). Our study takes a further step to reveal the “law” that governs the eye pointing performance under more general conditions, which can provide design implications, in addition to those of Zhang et al, for the user interfaces of gaze input. Next, we will give an overview of the related work of modeling eye pointing, present the new extension of  $ID_{eye}$ , report the results of our experimental evaluations, and discuss the implications for UI designs.

## 2 RELATED WORK OF MODELING EYE POINTING

Although a number of studies investigated the validity of Fitts' law for eye pointing (Ware 1987; Miniotas 2000; Vertegaal 2008; Zhai 1999; Gajos 2007; Zhang 2008), there was no research specifically addressed the issue of modeling eye pointing until Zhang et al.'s work. They indicated that the definition of  $ID_{eye}$  could be interpreted from two different perspectives. One was information theory (MacKenzie 1989; Seow 2005; Soukoreff 2004), the other was Meyer et al.'s theory about rapid aimed movement (Meyer 1988; Meyer 1990).

## 2.1 From the Perspective of Information Theory

Fitts was the acknowledged pioneer who applied the information theory to aimed movement and proposed the well-known Fitts' law (Fitts 1954), whose common form is the Shannon formulation expressed as follows.

$$MT = a + b \times ID = a + b \log_2(A/W + 1) \quad (2)$$

This form, as a theoretical tool in HCI, was proposed by MacKenzie (1992b). With respect to a communication system, the capacity of signal transmission channel from transmitter to receiver is defined by Shannon theorem 17 as follows (Shannon 1948):

$$C = B \log_2(S/N + 1) \quad (3)$$

where  $B$  denotes channel bandwidth,  $S$  is transmitter's signal power, and  $N$  means noise power. As can be seen, the definition of  $ID$  is an analogy to the channel capacity  $C$ .

Zhang et al. (2010) hypothesized that “the logarithmic function can be considered to be the ‘operator’ of the encoding and decoding process from the transmitter to the receiver”. Since the nervous signals relevant to eye pointing is transmitted only in the cranial nerve system, they viewed it as both the transmitter and the receiver in the pseudo communication system they assumed, i.e. the transmitter and receiver could be viewed as the same thing. Thus, they hypothesized that the encoding and decoding were unnecessary in the assumed communication system. In addition, Zhang et al. employed a conception of “signal enhancement” to account for the effect of effortless saccadic eye movements. Thus, they defined the “channel capacity” ( $C'$ ) of the information transmission in eye pointing as follows:

$$C' = B(S + S_0 + N) / N \quad (4)$$

Comparing Equation 4 with Shannon's theorem 17, there are the absence of the logarithmic function and the existence of a constant component  $S_0$ , which denotes the gain of signal enhancement. Zhang et al. did not provide a mathematical derivation for the definition of  $C'$ , but logically, it is reasonable.

Using the similar methodology of analogizing the Fitts  $ID$  to the classical definition of channel capacity (MacKenzie 1989), Zhang et al. initially defined  $ID_{eye}$  based on  $C'$  as follows:

$$ID_{eye} = (A + A_0 + W) / W \quad (5)$$

where  $A_0$ , as a distance constant, is the analogy to  $S_0$ . They hypothesized that  $A \ll A_0$  due to the little contribution rate of  $A$  to eye movement time as reported in various experiments (Sibert 2000; Gajos 2007; Zhang 20080, and that  $W < A$  in general. Thus, they simplified  $ID_{eye}$  to the following forms:

$$ID_{eye} = (A + A_0 + W) / W \Rightarrow ID_{eye} = e^{\lambda A} / W \quad (6)$$

where  $\lambda$ , as an empirical constant, is the replacement of  $1/A_0$ . Taking the instability of the eye cursor into consideration, they introduced another empirical constant  $-\mu$  into the denominator  $W$  to compensate for the negative effect of the unstable cursor. It means that if target size is close to the threshold  $\mu$ , it will be impossible to perform the task. Equation 1 expresses their final definition of  $ID_{eye}$ .

The results of Zhang et al.'s experiments (2010) indicated that the accuracy of  $ID_{eye}$ , with an average  $R^2$  of 0.95, were satisfying and reliable under different dwell time conditions as well as different eye cursor control methods (Zhang et al. 2008). More importantly, both of the empirical constants  $\lambda$  and  $\mu$  were consistent and could be generalized across different situations to make the results of model fitting well. These two constants have meaningful interpretations for the features of eye pointing. Regarding  $\mu$ , Zhang et al. found that the grand mean of the observed diameters of the areas where the eye cursor was jittering inside the target (see Figure 1b) could be directly used as the value of  $\mu$ . In other words,  $\mu$  was a measurable and meaningful parameter in practice. With respect to  $\lambda$ , it varied from .0003 to .0007 to achieve the best model fitting, directly reflecting the feature of saccadic eye movements that movement distance relatively has little impact on movement time.

## 2.2 From the Perspective of Meyer et al.'s Theory

The information-theoretical point of view on aimed movement is still accepted in the community of HCI, though abandoned in psychology (Luce 2003). One of the most influential theories about aimed movements is the stochastic optimized submovement model proposed by Meyer et al. (1988). This model assumes that in a rapid aimed movement, there is a primary submovement programmed to stop at the center of the target and, if necessary, an optional corrective submovement. Based on Meyer et al.'s movement model, movement time can be closely approximated by

$$T = a + b\sqrt{A/W} \quad (7)$$

In their subsequent work (Meyer 1990), they extended this model to take account of multiple submovements as follows:

$$T = a + b(A/W)^{\frac{1}{n}} \quad (8)$$

where  $n$  denotes the number of the assumed submovements in aimed movement. The parameter  $n$  leaves a room available for eye pointing. Harris and Wolpert (2006) proposed that there was an optimal speed-accuracy trade-off in the evolved saccade trajectories of primates. In their opinion, the optimal control strategy will make the eye move immediately to eliminate positional error when viewing a stationary target. It means that eye pointing in general only needs one saccade (i.e. primary movement) to make the eyes rapidly fixate on the target, with much less frequency of subsequent corrective saccades (Buswell 1935). Therefore, Zhang et al. set  $n=1$  when using Equation 8 for eye pointing. They reported that it was able to express the impact of  $W$ , but not to that of  $A$  due to the disproportion between the duration and amplitude of saccades. Considering the features of saccades and eye jitters, they introduced two empirical constants into Equation 8 to accommodate their effects as expressed as follows:

$$T = a + b \times (A'_0 + A)/(W - \mu') \quad (9)$$

If  $A \ll A'_0$ , Equations 1 and 9 essentially are equivalent to each other. The results of their regression analyses have validated this point. It means that the stochastic optimized submovement model, with a minor revision, also can be used to interpret eye pointing.

## 2.3 Implications of $ID_{eye}$ for Gaze-based Interactions

With some useful implications, Zhang et al.'s work can benefit researchers and designers, especially those who are focusing on gaze-based interactions. First,  $ID_{eye}$  implies that gaze input interfaces do not have the property of scale independence (Accot 2003) unlike manual input interfaces. Second, similarly to Fitts' law,  $ID_{eye}$  also implies that decreasing  $A$  and/or increasing  $W$  can facilitate the target acquisition; but more importantly, it further reveals that it is more efficient to increase  $W$  than to decrease  $A$  in gaze-based interactions. Third, the empirical constant  $\mu$  in  $ID_{eye}$  implies that processing the signal noises of gaze input like the algorithms proposed in the work (Zhang2008) to stabilize the jittery eye cursor (i.e. decrease  $\mu$ ) is also an important way to improve the performance of dwell-based eye pointing. In addition, the performance model based on  $ID_{eye}$  can be used as a theoretical tool for gaze input device and user interface evaluations, like Fitts' law for manual input.

Zhang et al.'s work interpreted the rationality of  $ID_{eye}$  from different perspectives and verified its accuracy under different conditions, but left the model of 2D eye pointing unknown. In next section, we will present our new extension.

## 3 NEW MODEL CANDIDATES FOR 2D EYE POINTING

With respect to hand pointing, HCI researchers have made great efforts to accurately predict movement time depending on both target width ( $W$ ) and height ( $H$ ) (MacKenzie 1992a; Accot 2003; Yang 2010) or probability distribution of hitting targets (Grossman 2005). Among these efforts, the methodology of weighted  $\ell_p$ -norm used by Accot and Zhai (2003) is an effective solution to

seamlessly integrate  $W$  and  $H$  together into the definition of  $ID$ . The general form of their definition, using  $ID_{az}$  in this paper, is expressed as follows:

$$ID_{az} = \log_2 \left( \left[ \omega \left( \frac{A}{W} \right)^r + \eta \left( \frac{A}{H} \right)^r \right]^{1/r} + 1 \right) \quad (10)$$

where  $\omega$  and  $\eta$  are two weighted parameters, and  $r$  denotes the norm order ( $r \geq 1$ ).  $ID_{az}$  has several desirable properties describing the features of 2D hand pointing as Accot and Zhai pointed out (2003):

- **Scale Independency.** When  $A$ ,  $W$  and  $H$  increase or decrease at the same rate,  $ID_{az}$  can still remain constant, without causing the change of movement time.
- **Limit Tasks.** If one of the target dimensions is increasingly close to infinity,  $ID_{az}$  will converge to the one-dimensional form similar to the “standard” Fitts  $ID$ .
- **Dominance Effect.** When either  $W$  or  $H$  becomes increasingly small, it will dominate the difficulty of 2D pointing and make the impact of the other suppressed.
- **Duality of  $H$  and  $W$ .** The two dimensions, with similar nature, jointly determine the difficulties of 2D pointing.
- **Continuity.**  $W$  and  $H$  have continuous effects on movement time instead of stepwise or segmented.

They examined the accuracy of  $ID_{az}$  for twelve different forms of parameterization and found out that the weighted Euclidean model (i.e.  $r=2$  and  $\omega=1$ ), as Equation 11 expresses, was the most appropriate form. They reported that when the weight  $\eta$  was in the range of  $[1/7, 1/3]$ <sup>1</sup>, the model could achieve the best ability to predict movement time. An important finding of that study is the asymmetrical impact of  $W$  and  $H$  on movement time. It informs user interface designers that it is better to enlarge the width of a rectangular target than to increase the height (at least when the target is arranged in horizontal directions).

$$ID_{az} = \log_2 \left( \sqrt{(A/W)^2 + \eta(A/H)^2} + 1 \right) \quad (11)$$

Accot and Zhai's work motivates our current work and also gives us useful inspirations. We can easily use the methodology of weighted  $\ell_p$ -norm to extend  $ID_{eye}$  for 2D eye pointing. It is noteworthy that, however, the two weighted parameters  $\omega$  and  $\eta$  in Equation 10 are independent from each other. We believe that there should be some interrelation between the impacts of the two dimensions. A natural hypothesis is that the whole impact of the target depends on both dimensions and if one dimension's impact increases, the other dimension's impact will decrease equivalently. Thus, we can let  $\omega+\eta=1$ . With this revision, we directly redefine the index of difficulty for 2D eye pointing as

$$ID_{eye} = e^{\lambda A} \left( \frac{\omega}{(W - \mu)^r} + \frac{1 - \omega}{(H - \mu)^r} \right)^{1/r} \quad (12)$$

where the weight  $\omega$  is in the range of  $[0, 1]$ . This definition retains all the properties of  $ID_{az}$  except for that of scale independency, which is not available for eye pointing (Zhang et al. 2010). At the same time, there are additional properties as follows:

- **Backward Compatibility.** Regardless of  $\omega$  and  $r$ , the redefined  $ID_{eye}$  will be equivalent to the original form in Equation 1 if the target is a square or a circle. In other words, the original form is a special case of  $ID_{eye}$ .
- **Duality of the thresholds of  $H$  and  $W$ .** When either  $H$  or  $W$  is gradually decreased to a threshold ( $\mu$ ), the difficulty of the task will tend to infinity.
- **Complementarity of  $H$  and  $W$ .** When one target dimension's impact increases, the other dimension's impact will decrease equivalently, and vice versa.

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<sup>1</sup> Accot and Zhai conducted their experiment only in horizontal directions. Our two-dimensional Fitts' law study revealed that the parameter  $\eta$  would periodically vary with movement direction and that  $\eta$  would be greater than 1.0 in vertical directions.

In the new definition of  $ID_{eye}$ , except for the measurable parameter of  $\mu$ , there are still three parameters needed to be determined. With respect to  $\lambda$ , Zhang et al. (2010) pointed out that it was a very small decimal, but they did not give a reasonable range for this parameter. The suitability of the average estimate (.0005) of  $\lambda$  in Zhang et al.'s investigations is unclear for 2D eye pointing. Thus, we still treat it as a free variable. As for the weight  $\omega$  and the norm order  $r$ , besides treating them as two free variables, we consider some specific combinations of them, such as  $\omega=0.5$  and  $r \in \{1, 2, \infty\}$ , to find out a suitable parameterization scheme. Totally, we produce eight schemes, i.e. eight model candidates. When  $\omega=0.5$ , it means that  $W$  and  $H$  theoretically have equal impact. When  $r=2$ , we also call the corresponding expression (Equation 13) Euclidean model.

$$T = a + b \times e^{\lambda A} \sqrt{\frac{\omega}{(W - \mu)^2} + \frac{1 - \omega}{(H - \mu)^2}} \quad (13)$$

Next, we conduct two experiments to verify the accuracy of the eight different model candidates. Meanwhile, we also use Equations 11, with subtracting  $\mu$  from  $W$  and  $H$ , as a baseline for comparisons.

## 4 EXPERIMENT 1: EYE POINTING IN DIAGONAL DIRECTIONS

The main purpose of this experiment was to find out a suitable parameter combination for  $ID_{eye}$  to accurately reflect the difficulties of 2D eye pointing.

### 4.1 Apparatus and Subjects

The software and hardware configurations of the experiment were similar to those in Zhang et al.'s work (2008). As Figure 1a illustrates, we employed a head mounted eye tracker, *EyeLink II*, as the gaze input device. The tasks were presented on a 19-inch CRT display at 1024×768 resolution. The device worked in pupil-only mode at the sampling rate of 250 Hz. Twenty able-bodied participants (8 females and 12 males, with the average age of 24) successfully completed this experiment. All of them have normal or correct-to-normal vision.

### 4.2 Task and Procedure

The experimenter, who supervised the experiment process when the subject was performing the task, carried out a 9-point calibration at the beginning of the experiment, as well as a 1-point drift correction if necessary during the process, to output the coordinates of the line of sight on the display as accurate as possible. The task was to acquire a rectangular target by dwell-based eye pointing. For each trial, there was a trial-start button randomly appearing at one of the predefined positions on the screen. At first, the subject needed to look at the button for a very short time to explicitly begin a trial so that the target immediately appeared at a given position with certain distance in the diagonal direction, with the concurrent disappearance of the trial-start button. Then, the subject was asked to fixate on the target as soon as possible. If the cursor could continuously dwell on the target up to the threshold of dwell time (800 ms) within 5000 ms after the trial was started, a successful trial would be recorded. Otherwise, an error would be recorded. For each of the unsuccessful trials, it could be repeated for 5 times at most before suspending the experiment to recalibrate the eye tracker. At the end of each trial, the start button reappeared at a different position for next trial, with the target disappearing again.

As Figure 2 shows, the center of the target was marked with a small circle. The start button was presented as a 32-pixel-diameter solid circle, but its effective diameter was 120 pixels. The subject was instructed to focus on the two small circles in turn and avoid chasing the visible cross cursor. According to the investigation of Zhang et al. (2011), these feedback forms and instructions would not significantly bias the stability of the cursor (i.e. the empirical constant  $\mu$ ) but could make the subject feel better to acquire the target.

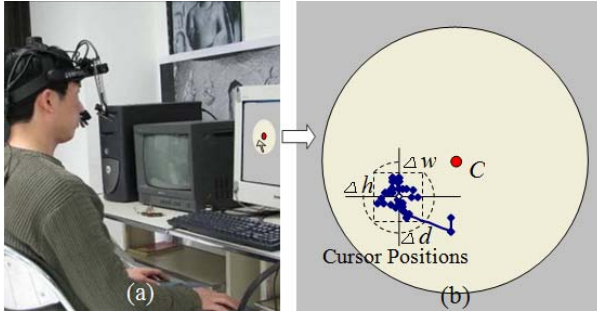


Figure 1. (a) A head-mounted eye tracker used as pointing device. (b) The dwelling area of the eye cursor.  $\Delta d$  denotes the diameter if viewing the area as a circle;  $\Delta w$  and  $\Delta h$  denote the width and the height, respectively, if treating this area as a rectangle.

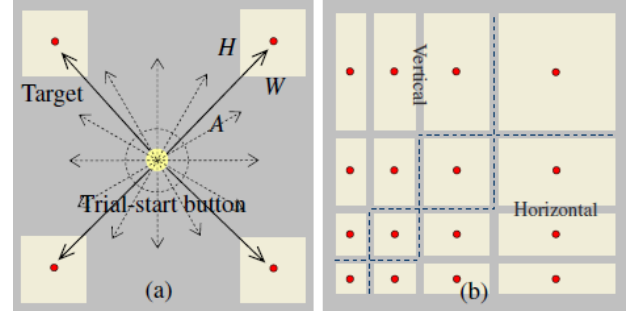


Figure 2. (a) Movement directions of the gaze. The dashed arrows denote the directions used in Experiment 2. (b) Target appearances.

### 4.3 Design

We employed a repeated measures within-subject design to reveal the user's capabilities of eye pointing. There were four explicit experimental factors: target width  $W$  (40, 56, 90, 160 pixels), height  $H$  (40, 56, 90, 160 pixels), gaze amplitude  $A$  (300, 600, 900 pixels) and eye cursor control method  $CCM$  (iSR vs. iSR')<sup>2</sup>. For each of the methods, there were 48 combinations of task conditions ( $4W \times 4H \times 3A$ ). All these combinations, with 2 trials for each, composed a block, within which the trials were presented in a random order. The subject needed to perform 7 blocks of trials under both of iSR and iSR' conditions. We counterbalanced the order of the control methods across all the subjects.

This experiment also included an implicit factor: target orientation. Figure 2b visualizes the variations of the target. As can be seen, there are six pairs of rectangular targets whose dimensions are the transpositions of each other. If the  $W$  and  $H$  ratio of the target  $> 1$ , we call it **horizontal** target; and if the ratio  $< 1$ , we call it **vertical** target.

### 4.4 Measures

Similar to the measures used in Zhang et al.'s work (2008; 2010), we also used the dependent variable of eye movement time ( $EMT$ ) as well as eye pointing time ( $EPT$ ) to express the human performance in 2D eye pointing.  $EMT$  denotes the time when the user's gaze is moving from the center of the trial-start button to that of the target. The corresponding movement distance, as Figure 2a shows, is the variable  $A$ . The unstable eye cursor might repeatedly leave and re-enter the target. For each trial, therefore,  $EMT$  was approximately measured from the start of the trial when the target appeared to the moment the cursor entered the target for the first time.  $EPT$  was measured from the start to the moment the cursor had continuously dwelt on the target for a given duration (800 ms) to activate the target. When the cursor was inside of the target, its positions were sampled at the rate of 25 Hz. As Figure 1b illustrates, if we view the small area where the sampled positions spread as a circle, we can calculate its diameter  $\Delta d$  for each trial; and if we view this area as a rectangle, we can calculate its width  $\Delta w$  and height  $\Delta h$ . These three measures reflect the eye cursor's stability when it is dwelling on the target.

<sup>2</sup> iSR' is a revision of iSR (Zhang et al. 2008). We expected that it could improve the human performance of eye pointing by making the cursor more stable (Zhang et al. 2010). Unfortunately, these two methods did not result in significant differences for all the measures we used. The details of iSR' are not presented due to the page limitation.



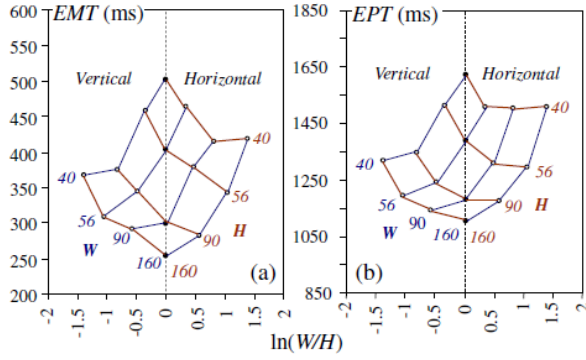


Figure 3. EMT and EPT by  $\ln(W/H)$ .

$r$	$\omega$	$a$		$b$		$\lambda$		$\omega, \eta$		$r$		$R^2$
		Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	
1	0.5	972.1	25.7	111.5	15.6	.0012	.0001	—	—	—	—	.885
	*	164.1	16.0	70.1	11.4	.0013	.0002	—	—	—	—	.886
		969.1	19.0	114.6	11.6	.0011	.0001	0.35	0.025	—	—	.939
2	0.5	163.6	14.8	70.5	10.6	.0013	.0001	0.40	0.034	—	—	.904
	*	989.9	25.4	110.5	14.5	.0011	.0001	—	—	—	—	.893
		158.4	16.4	69.8	11.3	.0013	.0001	—	—	—	—	.887
$\infty$	0.5	957.5	18.2	113.7	10.5	.0011	.0001	0.33	0.026	—	—	.946
	*	158.2	15.2	70.3	10.4	.0013	.0001	0.39	0.038	—	—	.905
		991.7	33.6	154.0	30.5	.0012	.0002	—	—	—	—	.810
*	0.5	179.7	21.3	94.1	23.2	.0015	.0002	—	—	—	—	.806
	*	977.4	26.2	164.9	23.8	.0012	.0001	0.43	0.013	—	—	.887
		173.6	19.4	99.0	21.1	.0014	.0002	0.45	0.015	—	—	.843
*	0.5	961.3	25.5	112.1	14.9	.0011	.0001	—	—	1.64	0.38	.895
	*	159.8	16.4	70.8	11.4	.0013	.0001	—	—	1.47	0.43	.890
		958.7	18.2	115.2	10.6	.0011	.0001	0.34	0.027	1.65	0.29	.948
Eq. 11	*	159.4	15.2	71.2	10.5	.0013	.0001	0.40	0.036	1.49	0.41	.908
		456.3	50.4	195.7	11.5	—	—	3.38	0.935	—	—	.877
		-112.2	25.4	122.1	6.4	—	—	1.90	0.435	—	—	.895

Table 1. Summary of model fitting for the data in Experiment 1 (results presented in each cell above for EPT and below for EMT)

## 4.5 Results

We excluded the error trials and the outliers, totaling about 4.5% of the whole data, from our analyses. The measure  $\Delta d$  as well as both of  $\Delta w$  and  $\Delta h$  was only used to determine the empirical constant  $\mu$ , and the overall error rate was very low (2.4%). Therefore, here we only present the effects of the different factors on EMT and EPT.

### 4.5.1 Eye Movement Time (EMT)

There was no significant learning effect in this experiment ( $F_{6,114} = 0.56, p = .762$ ). Regarding cursor control method (CCM), it had no significant main effect on EMT ( $F_{1,19} = 1.01, p = .328$ ). This agreed with the results in Zhang et al.'s previous studies (2008; 2010). The other three factors  $W$  ( $F_{3,57} = 107.36, p < .001$ ),  $H$  ( $F_{3,57} = 114.45, p < .001$ ) and  $A$  ( $F_{2,38} = 381.65, p < .001$ ) all had a significant main effect on EMT, and their interaction effects  $W \times A$  ( $F_{6,114} = 12.52, p < .001$ ),  $H \times A$  ( $F_{6,114} = 12.58, p < .001$ ) and  $W \times H$  ( $F_{9,171} = 2.72, p < .01$ ) were also significant. We did not find significant interaction effect between CCM and the other factors on EMT. For each of the factors that significantly affected EMT, post hoc pairwise comparison tests indicated that the differences between different levels were all significant. EMT was positively correlated to  $A$ , but negatively to both  $W$  and  $H$ . As depicted in Figure 3a, when  $W$  or  $H$  gradually increased, EMT would decrease in general. The significant interaction effect between  $W$  and  $H$  implied that both of them were not independent of each other to affect EMT.

### 4.5.2 Eye Pointing Time (EPT)

Compared with iSR, the revision iSR' unfortunately did not further benefit EPT ( $F_{1,19} = 3.48, p = .078$ ). Such a result was not as we had expected. It was similar to the effects on EMT that EPT was also significantly affected by  $W$  ( $F_{3,57} = 72.83, p < .001$ ),  $H$  ( $F_{3,57} = 194.38, p < .001$ ) and  $A$  ( $F_{2,38} = 234.51, p < .001$ ), with a significant interaction effect between each pair of them, especially that of  $W \times H$  ( $F_{9,171} = 2.40, p < .05$ ). The differences between different levels of these three factors were all significant except for that between the target width  $W$  levels of 90 and 160 pixels. As Figure 3b shows, the correlations of EPT with  $W$  and  $H$  were similar to those of EMT.

### 4.5.3 Vertical Targets vs. Horizontal Targets

As Figure 2b illustrates, the conditions of the target could be divided into three categories: vertical, square and horizontal. In order to reveal the effects of the factor of target orientation, we reorganized the data and excluded those under the square target condition. We found that both  $EMT$  ( $F_{1,19} = 0.60, p = .450$ ) and  $EPT$  ( $F_{1,19} = 0.02, p = .895$ ) were not significantly affected by target orientation under the condition of the target width and height combination of (40 pixels, 56 pixels), and that  $EMT$  ( $F_{1,19} = 3.23, p = .088$ ) was also not significantly affected under the combination condition of (90 pixels, 160 pixels). In other situations, target orientation had significant effect on both  $EMT$  and  $EPT$ . It seems likely that when the target's shape was close to a square, the effect of target orientation would become insignificant. As Figure 3 indicates, it was easier, in general, to acquire vertical targets.

### 4.6 Model Fitting

Before fitting the models to the observed data, we calculated the grand means of  $\Delta d$ ,  $\Delta w$ , and  $\Delta h$  under different  $CCM$  conditions, obtaining 17.5, 11.0, and 11.3 pixels for  $iSR$ ; and 17.2, 10.6, and 11.2 pixels for  $iSR'$ , respectively. They were very close to each other, which indirectly explained why  $iSR'$  did not result in further improvement for  $EPT$  (Zhang 2010). Therefore, we finally did not separate the data of  $iSR$  and  $iSR'$ , getting the grand means of 17.3, 10.8, and 11.3 pixels, respectively. Thus, when we viewed the dwelling area of the cursor as a rectangle, we could treat it overall as a square, with the average size approximate to 11.0 pixels.

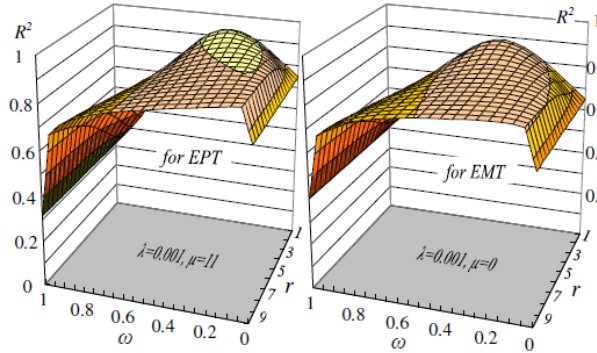


Figure 4.  $ID_{eye}$  model's fitness as a function of  $\omega$  and  $r$ .

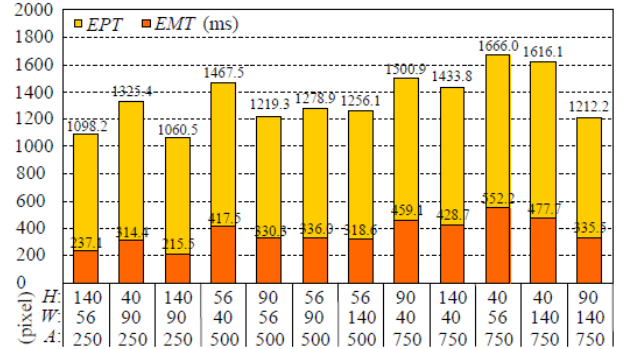


Figure 5. Averages of  $EMT$  and  $EPT$  by the combination of  $(A, W, H)$ .

As some of the experimental data were observed under the special condition of square target, we first picked them out to test the validity of the original  $ID_{eye}$  model (i.e. Equation 1). Under the condition of square target, the grand means of  $\Delta d$ ,  $\Delta w$ , and  $\Delta h$  were 18.7, 11.9, and 12.0 pixels, respectively. If we let  $\mu=18.7$  pixels and  $\lambda=.0005$ , similar to the settings of Zhang et al., we found that the  $ID_{eye}$  model had a good fit to the data, with a  $R^2$  of .933. If we viewed the dwelling area as a square, i.e. set  $\mu=12.0$  pixels, this model's accuracy, with a  $R^2$  of .946, had a slight improvement. Actually, this was reasonable due to the fact that the difficulty of acquiring a square target is smaller than acquiring a circular target with the same size because the former's area is bigger than that of the later. If we further treated  $\lambda$  as a free variable,  $R^2$  could obviously increase to the level of .983 when  $\lambda=.001$  (and  $\mu=12.0$  pixels). Therefore, we preferred to view the dwelling area as a square and the parameter  $\lambda$  as a free variable when fitting the  $ID_{eye}$  model to the experimental data.

According to the grand means of  $\Delta w$  and  $\Delta h$  above, we set  $\mu=11$  when fitting the models to the data of  $EPT$  and set  $\mu=0$  for the data of  $EMT$  since the duration of dwelling had been excluded from  $EMT$ . In addition, in order to make  $ID_{eye}$  in number comparable with  $ID_{az}$ , we magnified the former 80 times on the base of Equation 13. Table 1 summarizes the results of model fitting. As can be seen,  $ID_{eye}$  resulted in higher  $R^2$  especially when  $\omega$  was treated as a free parameter. More importantly, the estimates of the

regression coefficient  $a$  were unreasonable in the models of Equations 11. For  $EPT$ , they were smaller than the specified dwell time (800 ms), and even negative for  $EMT$ . These situations could lead to a negative prediction of  $EMT$  or a prediction of  $EPT$  that was smaller than 800 ms when the task was very easy. However, that is impossible in reality.

Therefore,  $ID_{eye}$  was suitable for 2D eye pointing. With respect to the different parameterizations of  $\omega$  and  $r$ , overall it was better to set  $\omega$  free than to preset  $\omega=0.5$ . At the same time, compared with the results in the situation of setting  $r$  free, the Euclidean model (Equation 13) was already good enough. According to the estimates of  $\lambda$  in different situations, it seems likely that we could fix it at the level of .001 to reach satisfactory results. As Figure 4 shows, we plotted  $R^2$  as a function of both  $\omega$  and  $r$ , which had a convex curved surface. We found that the Euclidean model was very close to the “optimal solution”, which the model’s  $R^2$ - $\omega$  curve contains the global maximum of  $R^2$ . Therefore, we finally give the most suitable model as follows:

$$T = a + b \times 80e^{0.001A} \sqrt{\frac{\omega}{(W - \mu)^2} + \frac{1 - \omega}{(H - \mu)^2}} \quad (14)$$

Experiment 1 demonstrated the goodness of  $ID_{eye}$ , and it also uncovered that the impacts of  $W$  and  $H$  were asymmetrical. More importantly, unlike the asymmetry in hand pointing (Accot 2003), it was target height  $H$  that had greater impact on the human performance of eye pointing because the estimates of  $\omega$  were less than 0.5. This point informed designers that it was more efficient to elongate target height to facilitate dwell-based eye pointing.

Movement direction is one of the important concerns of HCI researchers about 2D hand pointing (MacKenzie 1992a; Grossman 2005; Yang 2010). In this experiment, however, the movement directions of the subject’s gaze were limited at diagonal directions. How about  $ID_{eye}$  as well as the asymmetry of  $W$  and  $H$  under other different movement direction conditions? To answer this question, we carried out the next experiment.

## 5 EXPERIMENT 2: EYE POINTING IN VARIOUS DIRECTIONS

Compared with Experiment 1, the differences of this experiment were (1) that we replaced the CRT display with a LCD (1440 × 900 pixels), but maintaining the same pixel size (i.e. 5 pixels were about 1.65 mm or .135 degrees of visual angle); (2) that we did not fully cross the target conditions ( $W$ ,  $H$ ,  $A$ ) but carefully manipulated them to make the values of  $ID_{eye}$  spread as uniformly as possible in the corresponding range; and (3) that the experiment systematically tested all the target conditions in 12 different directions as depicted using the dashed arrows in Figure 2a. In addition, we only employed the method iSR’ to control the eye cursor.

As Figure 5 indicates, there were 12 combinations of ( $W$ ,  $H$  and  $A$ ). In this experiment, movement direction, denoted using  $\theta$ , was the only factor that fully crossed with those combinations. This experiment included 9 task blocks, of which each had 144 trials (12 combinations × 12 directions × 1 trial). Another group of 18 subjects (6 females and 12 males with the average age of 23) successfully finished the experiment within one session lasting about 45 minutes.

### 5.1 Results

We excluded the errors and the outliers (6.2% of the data) from the analyses. Figure 5 represents the averages of  $EMT$  and  $EPT$  for each of the twelve combinations of ( $W$ ,  $H$  and  $A$ ). The direction factor  $\theta$  had a significant main effect on  $EMT$  ( $F_{11,187} = 17.0$ ,  $p < .001$ ) as well as  $EPT$  ( $F_{11,187} = 3.8$ ,  $p < .001$ ). Post hoc pairwise comparisons indicated that  $EMT$  had significant differences in the majority (45 pairs) of the total pairs of directions, but so did  $EPT$  in the minority (23 pairs). We also noted that  $EPT$  had no significant difference between any pair of reciprocal directions, thus we pooled the corresponding  $EPT$  data when fitting the model of Equation 14.

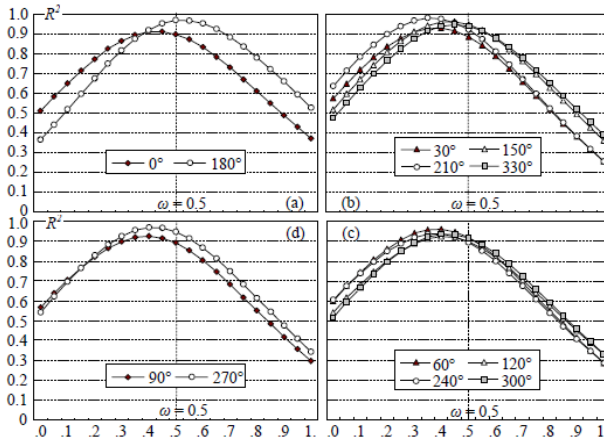


Figure 6.  $R^2$  plotted as a function of  $\omega$  for the data of EMT under every different  $\theta$  condition.

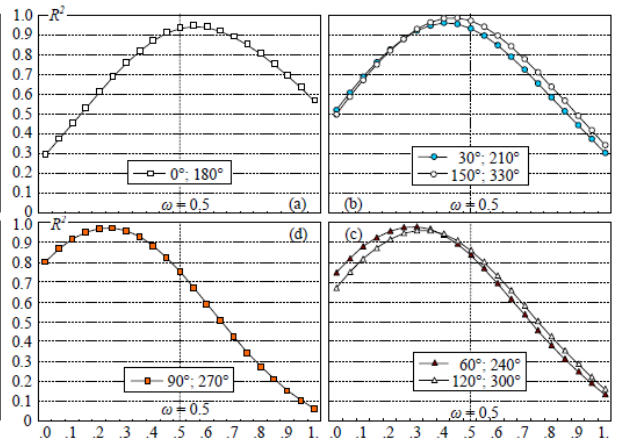


Figure 8.  $R^2$  plotted as a function of  $\omega$  for the data of EPT in different reciprocal directions.

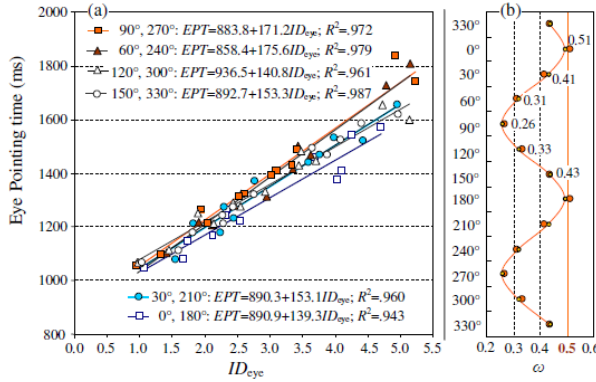


Figure 7. (a) Regression lines of EPT under different  $\theta$  conditions; (b) Estimates of  $\omega$  varying with  $\theta$ .

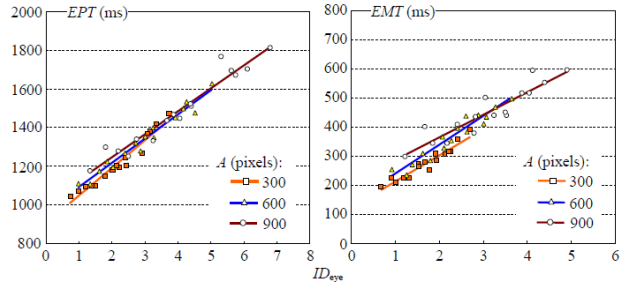


Figure 9. Regression lines of EPT and EMT under different  $A$  conditions in Experiment 1.

## 5.2 Asymmetrical Impacts of Target Width and Height in Different Directions

In this experiment, we sampled more than four hundred thousand coordinates of the eye cursor to calculate the parameter  $\mu$ . We found that  $\mu \approx 10$  pixels under every different  $\theta$  condition as well as for the pooled data. Thus, when fitting the Euclidean model (Equation 14) we let  $\mu=10$  and 0 for the data of EPT and EMT, respectively. Similar to the corresponding data of Experiment 1, this model could accurately predict the overall means of EPT and EMT ( $R^2=.992$  and  $.967$  when the weighted parameter  $\omega=0.365$  and  $0.413$ , respectively). This result confirmed that  $H$  overall had greater impact on eye pointing.

Importantly, we found that the Euclidean model could also accurately fit to the data ( $R^2>0.9$ ) under every different  $\theta$  condition, with the parameter  $\omega$  varying for the best accuracy. As Figures 6 and 8 show, we plotted  $R^2$  as a function of  $\omega$  to showcase the different abilities of the Euclidean model to predict EMT in every direction as well as EPT in every pair of reciprocal directions. As can be seen, these two figures directly indicate the duality of  $W$  and  $H$  because when  $\omega=0$  or  $1$  the model would be invalid. When the Euclidean model was achieving the best prediction,  $\omega < 0.5$  in general. That is to say,  $W$  and  $H$  usually had asymmetrical impacts on the performance under different  $\theta$  conditions, meanwhile,  $H$  in general was more critical than  $W$ .

Figure 7a depicts the regression lines of *EPT*, and Figure 7b illustrates the corresponding estimates of  $\omega$ . As can be seen, the performance in horizontal directions was the best, while the performance in vertical directions was the worst. Another interesting finding was that the estimates of  $\omega$  seemed to periodically vary with  $\theta$  as they could be closely approximated by  $\omega=0.258+0.233\cos^2\theta$  ( $R^2=.973$ ). It implies that  $W$  and  $H$  almost have equal impact ( $\omega \approx 0.5$ ) on *EPT* in horizontal directions, which also lead to the maximum impact of  $W$ . In addition, we can interpret the mathematical expectation (0.375) of the approximate expression as the overall impact of  $W$  (i.e.  $\omega = 0.365$ ).

## 6 DISCUSSION

We have successfully extended the 1D form of  $ID_{eye}$  (Zhang et al. 2010) to 2D dwell-based eye pointing tasks. The results of our study indicate that the redefined  $ID_{eye}$  can accurately model the human performance no matter whether or not the effect of movement direction has been neutralized.

Comparing the empirical constants ( $\mu$  and  $\lambda$ ) in the 1D and 2D forms of  $ID_{eye}$ , we need to point out the differences of them. For 2D eye pointing, we also directly calculated  $\mu$  using the sampled positions of the eye cursor. The difference was that we viewed the dwelling area of the cursor (see Figure 1b) as a small square, not a circle or a rectangle. In other words, we did not differentiate  $W$  and  $H$  when subtracting  $\mu$  from them to compensate for the effect of eye jitters. Our sampled data supported this decision.

With respect to another empirical constant  $\lambda$ , its value (.001) was different from that in Zhang et al.'s work (.0005). Actually, they did not conflict with each other. On the one hand, as we tested for the data under the square target condition in Experiment 1, it was able to accurately predict *EPT* when we let  $\lambda=.0005$ . On the other hand, if we let  $\lambda=.001$  for the data in Zhang et al.'s experiments, *EPT* as well as *EMT* also could be predicted well enough. Regardless of the concrete values of  $\lambda$  (.0005 or .001), they were determined based on a limited data set. Therefore, the key question is what is the potential requirement that the parameter  $\lambda$  has to satisfy. Zhang et al. (2010) have pointed out that there is no property of scale independence in eye pointing and that the benefit of expanding target is greater than reducing movement distance. Based on these two features of eye pointing, we can find out the concrete constraint on  $\lambda$ . To simplify the reasoning, we use the initial definition of  $ID_{eye}$  in Equation 6 to express the changed difficulties after the movement distance has been decreased and the target size has been increased at the same rate  $n$  ( $n>1$ ) as follows:

$$ID'_{eye} = \frac{e^{\lambda A}}{nW} < \frac{e^{\frac{\lambda A}{n}}}{W} < \frac{e^{\lambda A}}{W} = ID_{eye} \quad (15)$$

Thus, the potential requirement for  $\lambda$  is as follows:

$$\frac{e^{\lambda A}}{n} < e^{\frac{\lambda A}{n}} \Rightarrow \lambda A - \ln(n) < \lambda \frac{A}{n} \Rightarrow \lambda A(1 - \frac{1}{n}) < \ln(n) \Rightarrow \lambda < \frac{1}{A} \cdot \frac{n \ln(n)}{n-1} \quad (16)$$

As the lower limit of the term  $n \ln(n)/(n-1)$  is 1, if  $\lambda < 1/A$ , the logical expression above will always be true. In practice, we can directly use the inverse of the maximum of  $A$  as the upper limit of  $\lambda$  to justify whether or not the estimate of  $\lambda$  is reasonable. In our experiments, for example, the maximum of  $A$  is 900 pixels, so  $ID_{eye}$  still can properly maintain the fundamental features of eye pointing when we let  $\lambda=.001$ . As can be seen, the practical requirement  $\lambda < 1/A$ , i.e.  $A < A_0$ , relaxes the hypothesis  $A \ll A_0$  (Zhang et al. 2010).

Our experiments justify that the Euclidean model is the most suitable extension. As Table 1 shows, when  $r=1$ ,  $ID_{eye}$  could mathematically fit to the data well enough, but this situation would imply that  $W$  and  $H$  were independent of each other to affect eye pointing time. In fact, this did not agree with the findings that there were significant interaction effects between  $W$  and  $H$  in Experiment 1. Furthermore, if  $ID_{eye}$  employed only one of the target dimensions (i.e.  $\omega = 1$  or 0), the correlation between  $ID_{eye}$  and *EPT* as well as *EMT* would be weak as Figures 4, 6 and 8 demonstrate.

The weighted parameter  $\omega$  can properly reflect the asymmetrical impacts of  $W$  and  $H$  on 2D eye pointing in different directions, and consequently the Euclidean model can accurately describe the performance, without the necessary to neutralize the effect of movement direction. Besides the implications that Zhang et al. (2010) have pointed out (as we have reviewed in the third section), our findings can further benefit the development of gaze input user interfaces as well as the design of eye pointing experiments. Here, we highlight our additional implications and recommendations.

- **Elongate targets in vertical directions.**  $H$  has greater impact than  $W$  in general. As Figure 7b indicates, the asymmetry of  $H$  and  $W$  for  $EPT$  can become increasingly significant if  $\theta$  is gradually varying from horizontal to vertical directions. Figure 3 directly shows that increasing  $H$  is more efficient than increasing  $W$ .
- **Use different expansion factors for  $H$  and  $W$  in the technique of target expansion.** Dynamically expanding targets is a useful interface technique to overcome the limitation of screen space (McGuffin 2005), and especially it is also an effective solution for the signal noise problem of gaze input. Our study implies that this technique should differentially expand the two target dimensions to fully use the areas in vertical directions but save those in horizontal directions.
- **Arrange targets in horizontal movement directions of the eyes.** Figure 7a indicates that 2D eye pointing can get better performance in horizontal directions. It means that arranging targets in horizontal directions, e.g. on the right side of the screen, can make target acquisition faster.
- **Sample coordinates of the cursor when it is dwelling in targets to decide the empirical constant  $\mu$ .** Researchers can directly use the grand mean of the sizes of the cursor's dwelling areas as the empirical constant  $\mu$ , which reflects the extent of the cursor's instability. The dwelling areas should be viewed as squares instead of circles.
- **Avoid possible inconsistency of model parameter estimation.** With respect to the traditional Fitts' law experiments of hand pointing, Guiard (2009) pointed out that using different movement distances could make it unsafe to estimate Fitts' law parameters. Unfortunately, we also observed similar results in our experiments. As Figure 9 shows, we plotted the regression lines of  $EPT$  and  $EMT$  for each of the different  $A$  levels in Experiment 1, demonstrating the obvious variations of the parameters. In addition, Figure 7a indicates that varying movement direction can also result in this problem. Therefore, we recommend to fix the level of  $A$  in eye pointing experiments and perform the task only in specific directions, such as the diagonal directions. This is a safer design policy when gaze input conditions are to be compared.

## 7 CONCLUSIONS

There have been a number of applications of gaze input, but there is lack of an effective tool to guide the development of gaze-based interactions until Zhang et al.'s work (2010). In this paper, we further extend their 1D definition about the index of difficulty for eye pointing ( $ID_{eye}$ ) to take account of arbitrary 2D rectangular targets. We carry out two experiments to verify the accuracy of our new extensions and justify the following Euclidean form as the most appropriate one.

$$ID_{eye} = e^{\lambda A} \sqrt{\frac{\omega}{(W - \mu)^2} + \frac{1 - \omega}{(H - \mu)^2}}$$

The weighted parameter  $\omega$  can properly capture the asymmetrical impact of target width and height on eye pointing, with the later exceeding the former in general, even when the effect of movement direction are explicitly involved in the task instead of being eliminated. We discuss how to determine the empirical constants  $\lambda$  and  $\mu$ , which reflect the features of saccades and eye jitters. According to our findings, we provide practical design guidelines for user interfaces in addition to those of Zhang et al. and also offer some design recommendations for eye pointing experiments.

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