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MODELLING SELECTION TASKS AND ASSESSING PERFORMANCE IN WEB INTERACTION

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ABSTRACT

The paper suggests a model for selection tasks that are widespread in modern interaction on the WWW, as well as the means to evaluate performance as human processor throughput. Selection tasks are considered the combination of choice and movement stages, which are traditionally modelled with Hick-Hyman and Fitts' laws respectively. However, as the former seems to fall short in most real interactions, we propose the model based on visual search time (VST) instead. Search area size (S_0), sought element size (S) and the number of alternatives (N) were elected as primary factors for VST, although vocabulary size and number of search keys are also considered. In the result of experimentation with 28 subjects of different age groups, VST was suggested as the logarithm of the ratio between S_0 and S, with N not being significant. Index of selection difficulty (IDS) is proposed based on Fitts' ID, as well as subsequent notion of selection throughput (TPS), whose mean value in the experimentation amounted to 12.6 bit/s. The models might assist in creating more usable web interfaces, justifying interface elements' and blocks' sizes and hierarchy and allowing the evaluation of various interface designs via selection tasks throughput performance measure.

KEYWORDS

Fitts' Law, Hick-Hyman Law, Model Human Processor, Throughput.

1. INTRODUCTION

The emergency of the influential Claude Shannon's Theory of Information (1949) led to the development of information processing approach to human cognition and behaviour (Huitt, 2003). In the field of Human-Computer Interaction (HCI), the model human processor (Card et. al, 1983) could be applied to describe composite interaction tasks. E.g., selection tasks, which are prevalent in many modern interfaces (with mouse or touch-screen, etc.), may be represented as combination of choice and movement stages. The two models that survived the initial information theory fad in psychology are Fitts' and Hick-Hyman laws (MacKenzie 1992, p.95; Seow, 2005), which model movement and choice reaction time respectively, but their applicability remains unequal, as we'll elaborate further.

1.1 The Fitts' Law

Paul Fitts (1954) proposed to measure difficulty in rapid aimed movement tasks by analogy with information transmission, based on Claude Shannon's 17th theorem (1949), so that movement amplitude (A) corresponds to signal power, while allowed variation of the movement, i.e. the size of the area where the movement ends, (W), – to noise power. Thus was formulated the index of difficulty (ID) for movement tasks:

$$ID = \log_2(A/W + 1) \qquad (1)$$

Equation (1) was proposed by MacKenzie (1992). It is both in better conformity with Shannon's theory and seems to provide closer fit to empirical data than Fitts' original one. Fitts sought to obtain the measure for motor system "capacity" and introduced the index of productivity (IP), as the ratio between ID and corresponding movement time (MT):

$$IP = ID / MT \qquad (2)$$

In Fitts' law experiments, MT is usually the dependent variable, while A and W are independent variables. The relation between MT and ID is found with regression:

$$MT = a + b * ID = a + b * \log_2(A/W + 1), \qquad (3)$$

where a and b are regression coefficients. Equation (3) is one of the popular formulations of Fitts' law, stating that time required to make a rapid aimed movement is proportional to logarithm of the distance to target (A) divided by the target width (W). An important subsequent development was the introduction of effective index of difficulty (ID_e), based on effective target width (W_e) adjusted for movement accuracy (details are provided in Soukoreff and MacKenzie, 2004). Thus the index of performance, which is commonly called throughput (TP), averaged between K subjects and M outcomes for each combination of A and W, is a complete measure of performance, embracing both movement speed and accuracy:

$$TP = 1/K \sum_{i=1}^{K} (1/M \sum_{j=1}^{M} \frac{ID_{eij}}{MT_{ij}}) \qquad (4)$$

The correspondingly computed throughput for various interactions devices ranges from 3.7 to 4.9 bit/s for mouse, 1.0–2.9 for trackball, 1.6–2.6 for joystick, etc. (Soukoreff and MacKenzie 2004, p.784).

1.2 The Hick-Hyman Law

W.E. Hick (1952), who was one of the first to apply Information theory to psychological problems (Seow 2005, p.322), noted that reaction time (RT) when choosing from N equiprobable alternatives is proportional to the logarithm of their number :

$$RT \sim k * \log_2(N+1), \qquad (5)$$

where k is the rate of gain of information. Afterwards, Ray Hyman (1953) generalized this rule, reasonably articulating that RT in fact is linearly related to information quantity, i.e. the entropy of the set of stimulus (H_T):

$$RT = a_H + b_H * H_T, \qquad (6)$$

where a_H and b_H are empirically defined constants. The slope in thus formulated Hick-Hyman law (6), b_H, in simplest cases is believed to be equal to 150 ms (Longstreth et. al, 1985), then the corresponding Hick's rate of gain of information (b_H^{-1}) is equal to 6.7 bits/sec. There are, however, evidences that the rate varies significantly due to subjects' age, gender, training, arousal, fatigue, etc., as well as to concurrent cognitive processes, distractions, and stimulus type and intensity (Welford, 1980).

1.3 Application for HCI and Usability Engineering

Despite the lack of a satisfactory psychomotor theory to support Fitts' law, it provides very good fit to empirical data and applies to wide variety of conditions. As such, the law is extensively used in HCI practice (review is available, e.g., in Seow, 2005), both as predictive model for movement performance time, and to compare throughput in various experimental settings (e.g., for different interaction devices). For usability engineering models seeking to predict performance time for more elaborate interaction tasks (such as KLM-GOMS human information processor models), Fitts' law adequately models movement sub-stages, but for choice sub-stages it's the Hick's law that falls short.

The most apparent difficulty in Hick-Hyman law practical application lies in the necessity to compute the quantity of information that needs to be processed (H_T in (6)), which is far more complex than $\log_2(N+1)$ for any real tasks (Seow 2005, p.341). Indeed, there are certain cases when the classic Hick-Hyman law was found to be well applicable, such as selecting from specially modeled menus, containing integers and alphabetically ordered words (Landauer and Nachbar, 1985). However, these don't seem practical enough for up-to-date interactions that involve compound visual interfaces, so enhancements to the law are generally required. In (Cockburn et. al, 2007), convincing results were obtained for interaction with specific interfaces (menus), by introducing distinct visual search time in the model and adding a factor reflecting degree of user experience – it has been shown e.g. by Longstreth et. al (1985) that for unknown alternatives RT increases linearly with N, but has almost no increase for well-known options. Summarizing, we'd like to conclude that usability engineering needs a tool to model widespread selection tasks, but Hick-Hyman law seems far from being instrumental in modern practice. Our paper puts forward alternatives to the law, and suggests the means to evaluate human performance in related interactions, which could assist researchers and usability engineers in building and comparing various interface design alternatives.

2. METHOD

2.1 Visual Search Time

We propose a model for selection time (ST) that is based on the combination of MT predicted by Fitts' law and visual search time (VST) as choice reaction component:

$$ST \sim c_1 * VST + c_2 * MT \, , \qquad (7)$$

where coefficients c_1 and c_2 are necessary to accommodate for possible interference and parallelism between the two processes. Further, we argue that decision time, as represented by Hick-Hyman law, is relatively neglectable for selection tasks in modern interaction. So, web interfaces that typically contain standard (familiar to users) elements, presumably place more burden on visual search rather than decision-making. Attempts to model visual scan time with Hick-Hyman law, such as by Soukoreff and Mackenzie (1995) for text entry tasks, were subsequently reconsidered (MacKenzie and Zhang, 2001), and though some modifications to the law were fruitful (Cockburn et. al, 2007), we feel a need for a new formulation.

There is no lack of research on visual search time and its applications in HCI (e.g., see Sears, 2001). The list of influencing factors, however, is generally not exhaustive and includes: the number of objects, size of vocabulary (i.e. the number of available different objects), number of search keys (utilized distinct features), display size (search area), as well as environment factors (illumination, contrast) and human personal attributes, such as age, experience (Trick and Enns, 1998). Thus visual search time model for an interface consisting of standard elements could be proposed as the following:

$$VST = f(N, n, k, S_0, S) = a_{VS} + b_{VS} * ID_{VS} \, , \qquad (8)$$

where N is number of objects, n – vocabulary size, k – number of keys, S_0 – work area size, S – sought element size; ID_{VS} is index of difficulty for visual search tasks, a_{VS} and b_{VS} are empirically defined constants. The model for ST, based on (7) and (8), may be written as the following:

$$ST = a_S + b_S * ID_e + c_S * ID_{VS} \qquad (9)$$

where a_S, b_S and c_S are constant defined with regression. Further, we propose index of selection difficulty (IDS) that contains Fitts' ID, ID_{VS} and weight coefficient (c) reflecting relative difficulty of movement and choice components in given selection task conditions:

$$IDS = ID_e + (c_S / b_S) * ID_{VS} = ID_e + c * ID_{VS} \qquad (10)$$

Then, we should be able to calculate throughput for selection task (TPS), similarly to (4):

$$TPS = \frac{1}{K} \sum_{i=1}^{K} \left(\frac{1}{M} \sum_{j=1}^{M} \frac{IDS_{ij}}{ST_{ij}} \right) \qquad (11)$$

2.2 Hypotheses

To confirm our reasoning, we identified several hypotheses to be checked in the subsequent experimental investigation:

H1. There is performance difference (time, accuracy) between movement and selection tasks.

H2. Hick's law is not adequate to model selection time.
H3. Visual search time is appropriate addition to movement time in modelling selection tasks (7).
H4. The proposed model is robust enough to plausibly model performance for different user groups.
H5. Movement (4) and selection (11) throughputs correlate per subjects and are affected by identical factors.

To confirm or refute the above hypotheses, as well as to define exact formulations for ID_{VS} and IDS, we undertook pilot investigation, in which we modeled movement and selection interaction tasks. Based upon the hypotheses and positioned in web interaction domain, in the experimentation we would alter N and S, while keeping n, k and S_0 constant. Further, to explore the effect of human personal attributes, we employed elder adults in the experiment, because there are evidences that this demographic group is distinct in terms of visual search (Trick and Enns, 1998).

2.3 Experimental Investigation

2.3.1 Subjects

Twenty eight subjects took part in the experiment. Fifteen participants (4 male, 11 female) were elder people and their age ranged from 56 to 74 (M=63.4, SD=5.26), recent graduates of 36-hour computer literacy courses held by People's Faculty of Novosibirsk State Technical University (NSTU). Thirteen subjects (5 male, 8 female) were recruited among NSTU students and general staff. They ranged in age from 17 to 30 (M=23.9, SD=4.38). All subjects had normal or corrected to normal vision. Eight (53.3%) elder subjects reported having no experience in using computers or mouse before the computer literacy courses.

2.3.2 Experiment Design and Procedure

The experiment consisted of two parts: in the first (control) one the subjects were assigned typical movement tasks modeled with Fitts' law, while in the second one the participants were asked to perform selection tasks. The general experiment design was carried out in accordance with recommendations for Fitts' law experiments, provided by Soukoreff and MacKenzie (2004). It was within-subjects, with two groups of participants – elder people and younger computer users. Before the experiment, data regarding the participants' age and gender were gathered. All subjects participated in the experiment voluntarily, and prior to the experimentation informed consents were obtained. Each subject then did a test run of trials with random combinations of A, W and N, until fully understanding the assignment, to negate the effect of practice.

In the first experiment, the two main independent variables were size of a square target (W: 8, 16, 32, 64, 128) and distance to it (A: 64, 128, 256, 512, 1024). There were 7 different ID values (not all combinations were used), ranging from 1.58 to 7.01. The number of outcomes for each combination of A and W was lower than generally recommended (15 for each of ID values), because of the exploratory nature of the study and the intent not to tire the seniors.

The subjects were presented with two squares, a starting position and a target, dissimilar in shape and color. They were positioned randomly in relation to each other on a computer screen to negate the effect of movement direction. The subjects were asked to click the starting position with a mouse pointer and then, “as fast and as accurately as possible”, move the pointer to the target and click it. Coordinates of both clicks were recorded; also if the second click was outside the target, error was recorded, and participant was taken to a next trial. The dependent variables were performance time (MT, between the two clicks) and error (E_1).

In the second experiment, the target would become visible on the screen only after participant’s click on the starting position. False alternatives (of dissimilar shape and color, all of them identical, so overall vocabulary size n=2) would appear together with the target. The number of alternatives was additional independent variable with 3 levels (N: 2, 4, 8), which were so far deliberately chosen not to exceed Miller’s number of 7±2. Also, there were A and W resulting in 6 different values of ID, ranging from 1.58 to 6.02, with 17 outcomes for each level of N. Again, the dependent variables were performance time (ST, between the two clicks) and error (E_2, clicks outside the target).

To measure and record the values of independent and dependent variables, an online application was developed with PHP and MySQL and used in IE web browser, with performance time measured with JavaScript to eliminate any server-side delay. The sessions with the two groups of participants, elder and younger, took place with 21-days interval in a same room on same computer equipment, with monitor screen resolution of 1024*768 pixels (thus constant S_0 of 1000*600 pixels).

3. RESULTS

3.1 Descriptive Statistics and Factor Effects

The 15 outcomes for each of 7 ID values in the first part of the experiment resulted in 105 data for each participant, producing a total of 2940 data, of which 2888 (98.2%) were considered valid. Invalid were the outcomes when subjects made an obviously erroneous click far from target or when the registered time was higher than 3000 ms. Table 1 shows mean values for movement time (MT) and error level (E_1) per ID as well as overall ones.

Table 1. Mean MT and E_1 per Fitts’ ID

ID	1.58	2.32	3.17	4.09	5.04	6.02	7.01	**Mean (SD)**
MT, ms	468 (251)	617 (303)	777 (379)	890 (374)	1039 (395)	1247 (483)	1425 (507)	922 (503)
E_1, %	3.4	5.6	4.6	4.8	5.6	6.8	11.0	6.0

MANOVA was used to test the effect of subjects’ characteristics such as subject group (elder or younger), gender and experience (for this factor, the analysis was done for elder participants only) on MT and E_1 (Table 2). The effect of the experimental conditions in the first experiment was analyzed independently for the two subject groups. Predictably, distance (A) had significant effect on MT for both elder and younger participants. At the same time, the effect of distance was not significant for the number of errors committed by neither seniors

($F_{6,1502}$=.9; p>.5), nor their younger counterparts ($F_{6,1336}$=1.2; p=.29). Size of target (W), besides significantly affecting MT for both subject groups, also had significant effect on error level for both elder ($F_{4,1502}$=5.5; p<.001) and younger participants ($F_{4,1336}$=2.7; p=.03). Post-hoc analysis indicated that only W=8px was significantly different in terms of committed errors, for both groups, and led to 10.2% and 12.3% errors for elder and younger subjects respectively. The interaction between distance to target and its size was not significant for either of the subject groups.

Table 2. MANOVA results (significance and est. marginal means) for MT and E_1 per subjects' characteristics

		All participants				Elder[1]			
		Group		Gender		Experience		Gender	
		Elder	Younger	Male	Female	Normal	Low	Male	Female
MT	Sig.	$F_{1,2884}$=890.9; **p<.001**		$F_{1,2884}$=8.1; **p=.005**		$F_{1,1523}$=121.4; **p<.001**		$F_{1,1523}$=9.3; **p=.002**	
	Est. mean, ms	1156	642	874	923	1016	1370	1242	1144
E_1	Sig.	$F_{1,2884}$=11.7; **p=.001**		$F_{1,2884}$=17.3; **p<.001**		$F_{1,1523}$=3.7; p=.06		$F_{1,1523}$=16.2; **p<.001**	
	Est. mean	3.7%	7.0%	3.4%	7.3%	5.0%	2.4%	1.0%	6.5%

The number of outcomes for each participant in the second part of the experiment was 51, producing a total of 1428 data, of which 1408 (98.6%) were considered valid. Table 3 shows means for selection time (ST) and error level (E_2) per ID and number of targets (N) as well as overall ones.

Table 3. Mean ST (ms) and E_2 (%) per N and Fitts' ID

ID **N**	1.58	2.32	3.17	4.09	5.04	6.02	**Mean (SD)**
2	842 (318) 3.6%	965 (423) 7.2%	1016 (409) 6.4%	1064 (283) 8.4%	1238 (405) 7.3%	1467 (530) 7.1%	1034 (414) 6.6%
4	814 (338) 4.8%	953 (432) 2.8%	1016 (426) 3.7%	1121 (379) 9.5%	1259 (399) 7.1%	1660 (558) 14.3%	1051 (459) 5.7%
8	797 (315) 4.8%	977 (480) 6.4%	1020 (392) 9.1%	1170 (424) 8.4%	1328 (478) 7.1%	1526 (439) 24.0%	1061 (461) 8.1%
Mean (SD)	818 (323) 4.4%	965 (444) 5.5%	1018 (408) 6.4%	1118 (368) 8.8%	1275 (428) 7.2%	1552 (514) 14.8%	1049 (444) 6.8%

[1] For elder subjects, also interaction between experience and gender was significant for MT ($F_{1,1523}$=6.8; p=.01)

As in the first part of the experiment, a multivariate analysis of variance was used to test the effect of subject group and gender on ST and E_2. The results suggest highly significant effect of subject group on time ($F_{1,1404}$=365.8; p<.001), with estimated marginal means of 1238 ms for elder subjects vs. 814 ms for younger ones. The effect of subject group on error was not significant ($F_{1,1404}$=1.8; p=.18), in contrast to the first part of the experiment. The gender factor remained significant for both ST ($F_{1,1404}$=5.3; p=.022) and number of committed errors ($F_{1,1404}$=5.0; p=.026). As before, male participants on average were somehow faster, with 1001 ms vs. 1051 ms for female ones. The mean number of errors was 4.6% and 7.8% respectively. No significant interaction between the independent variables was observed. The analysis for the effect of experimental conditions (A, W and N) is provided below.

3.2 Fitts' Law Regression and Throughput

To adjust the results for accuracy, effective index of difficulty (ID_e) was evaluated for each outcome as proposed by Soukoreff and MacKenzie (2004, p.755), but standard deviation of end-clicks was determined for each participant instead of for each condition. The mean value for ID_e was 3.81 (SD=1.82), and ID_e was used instead of nominal ID in Fitts' law regressions for elder (MT_{eld}; R^2=.493) and younger (MT_{yng}; R^2=.644) subjects:

$$MT_{eld} = 400 + 199 * ID_e \qquad (12)$$

$$MT_{yng} = 139 + 135 * ID_e \qquad (13)$$

All the coefficients in the above models were highly significant (p<0.001), and throughput (TP) was calculated for each subject as mean ratio between ID_e and MT for each outcome (4). The mean TP for all participants in the experiment was 4.53 (SD=1.41). The factors of age group ($F_{1,22}$=76.8; p<.001) and experience ($F_{1,22}$=11.6; p=.003) were significant for TP in ANOVA test, unlike the factor of gender ($F_{1,22}$=1.27; p=.272). Thus regression model was proposed for TP with factors of subjects' age (T) and low experience (LE, either 0 or 1). The model incorporated both age groups of participants and had highly significant coefficients (p<.001) and relatively high R^2=.904:

$$TP = 7.00 - 1.14 * LE - 0.05 * T \qquad (14)$$

3.3 Selection Time Analysis

To draw appropriate connections between MT and ST, we extracted conditions with ID ranging from 1.58 to 6.02 from the first part of the experiment, thus computing MT' and E_1'. The performance times and error levels per two experiment designs and subject groups are presented in Table 4.

Table 4. Dependent variables in the two experimental parts

	MT', ms	**E_1', %**	**ST**		**E_2**	
			ms	**change**	**%**	**change**
Elder	1067	3.6	1254	+17.5%	6.3	**+75.0%**
Younger	583	6.9	819	+40.5%	7.4	+7.2%
Overall	839	5.2	1049	+25.0%	6.8	+30.8%

To check if ST is well explained merely by Fitts' movement component, we computed effective index of difficulty, ID'_e, for second part of the experiment (mean ID'_e, was 2.89, SD=1.28). Then we attempted regression analysis with ID'_e, as the factor, for elder (ST_{eld}; R^2=.180; adj. R^2=.179) and younger (ST_{yng}; R^2=.299; adj. R^2=.298) participants:

$$ST_{eld} = 820 + 151 * ID'_e, \qquad (15)$$

$$ST_{yng} = 464 + 122 * ID'_e \qquad (16)$$

Comparing (15) with (12) and (16) with (13), we'd like to highlight sharp drops in R^2, i.e. the share of variation in performance time explained by the movement difficulty factor, as well as decrease of b values (slopes in Fitts' law).

3.4 Visual Search Time and IDS

To further examine the effect of N on ST (which did not clearly manifest in Table 3), we ran MANOVA test with ST and E_2 as dependent variables and N, W and A as factors. We found no significant effect for N on neither ST ($F_{2,1357}$=.27; p=.76), nor E_2 ($F_{2,1357}$=1.03; p=.36). The effect of W was highly significant for both ST ($F_{3,1357}$=131.36; p<.001) and E_2 ($F_{3,1357}$=6.05; p<.001). Movement amplitude A significantly affected ST ($F_{3,1357}$=23.51; p<.001), but not E_2 ($F_{4,1357}$=2.04; p=.09).

We attempted preliminary regression models for ST with $\log_2(N)$ and ID'_e as factors, and N was not significant in the regression (p=.308), so we decided to exclude the number of objects from the visual search time model (8). Then, we proposed the index of visual search difficulty (ID_{VS}) in the following form (not considering the factors of vocabulary size and number of search keys so far):

$$ID_{VS} = \log_2(S_0 / S) = \log_2(S_0 / W^2), \qquad (17)$$

where S is equal to W^2 in case of our square targets. The justification is twofold:

1. The S_0/S represents the "length" of graphic interface as a message, i.e. the maximum number of elements of square S that it can contain. It seems reasonable to assume that users "process" not just the displayed objects, but the whole interface, including whitespace. Then S_0/S should take the place of N in Hick's law (5).

2. Parallels may be also drawn with motor behaviour described by Fitts' ID (1): then "search amplitude" S_0 corresponds to A and "search termination area" S – to W.

Thus, IDS (10) will increase as target size diminishes, and approach Fitts' ID as target size grows. To determine the c coefficient in (10) for our experimental conditions (in particular, S_0=1000*600=600,000), we built regression models with ID'_e and ID_{VS} as defined in (17), for ST (R^2=.238; adj. R^2=.236; $F_{2,1405}$=218.9; p<.001), and separately elder (ST_{eld}; R^2=.293; adj. R^2=.291; $F_{2,743}$=158.8; p<.001) and younger (ST_{yng}; R^2=.427; adj. R^2=.426; $F_{2,659}$=245.9; p<.001) subjects:

$$ST = 90 + 81 * ID'_e + 69 * ID_{VS}, \qquad (18)$$

$$ST_{eld} = 136 + 87 * ID'_e + 82 * ID_{VS}, \qquad (19)$$

$$ST_{yng} = 27 + 77 * ID'_e + 53 * ID_{VS} \qquad (20)$$

So, from (18), IDS in our experimental conditions will be:

$$IDS = ID_e + (69/81) * ID_{VS} = ID_e + 0.85 * ID_{VS} \qquad (21)$$

Mean value for IDS thus defined was 11.9, SD=2.69.

3.5 Selection Task Throughput

Having IDS values, we were able to calculate selection task throughput, as proposed in (11). The mean TPS for all participants in the experiment was 12.6 (SD=3.04). The correlation between TP and TPS per participants was quite high and amounted to .916. The factors of age group $F_{1,22}$=39.8; p<.001) and experience level ($F_{1,22}$=5.97; p=.023) were significant for TPS in ANOVA test, unlike the factor of gender ($F_{1,22}$=.8; p=.78). Correspondingly, regression model was proposed for TPS with factors of subjects' age (T) and low experience (LE, either 0 or 1). The model incorporated both age groups of participants and had highly significant coefficients (p<.001) and relatively high R^2=.88:

$$TPS = 17.9 - 2.27 * LE - 0.104 * T \qquad (22)$$

4. CONCLUSIONS

The pilot experimental investigation undertaken with 28 subjects of two distinct age groups performing movement and selection tasks, allowed us to draw some conclusions regarding the formulated hypotheses.

4.1 Hypotheses Check Results

H1. Confirmed. Selection tasks took more time to complete and the accuracy was lower (Table 3) than for movement tasks. We'd like to note that the increase in performance time was nearly constant for the two subject groups, 187 ms for elder vs. 236 ms for younger participants, but the growth in error level for senior subjects was far more dramatic, at +75.0%, which may be explained by poorer multi-tasking abilities of people in older age.

H2. Confirmed. The number of alternatives (N) didn't have significant effect on ST, and $\log_2(N+1)$ was not significant in the regression.

H3. Partially confirmed. ID_{VS}, as proposed in our paper (see (17)) was significant in regression for ST, but the resulting R^2 were lower than for movement tasks.

H4. Confirmed. ST regressions with ID_{VS} factor were significant for both elder (19) and younger (20) subjects, and regression coefficients suggest that visual search task is relatively harder for seniors than movement task. This corresponds well to sharp increase (+75%) in error level for elder participants in selection tasks.

H5. Confirmed. Movement and selection throughputs are relatively highly correlated per subjects, and the effects of age and experience on TP and TPS (see (14), (22)) are similar.

4.2 The Study Validity

The R^2 values produced in our study were relatively low, which is especially uncommon for Fitts' law models that generally manifest R^2 of .9 and higher (Soukoreff and MacKenzie 2004, p.768). It may be possibly explained by modest number of participants in the experiment, as well as imperfections in utilized software and software mouse acceleration, which could introduce random bias in time measurements.

It is not entirely clear if IDS may be considered entropy for selection tasks, but the obtained mean value for proposed selection task throughput, 12.6 bit/s, seems to be consistent with established human visual processing capacity that ranges from 5 to 70 bit/s. It is known that tasks requiring deeper processing have lower capacity: perception of TV picture is at 50-70 bit/s, simple text reading – 40-50 bits/s, while text proof-reading – 18 bit/s (Gasov and Solomonov 1990, p.62), so TPS was to be expected in the lower part of the range.

4.3 Research Prospects

The model for selection time (9) and the formulation of ID_{VS} (17) proposed in our study are subjects for further development. In particular, the factor of vocabulary size (n) will need to be included if visual search is viewed from information processing perspective. Also, further exploration of work area size effect (S_0) is likely to have practical significance, since varying this factor corresponds to usage of interface blocks, which is a mainstream in modern interface design. However, even in the current form, ID_{VS} may be used to justify choosing interface elements and blocks sizes, as well as optimal blocks hierarchy, while IDS provides means for measuring selection tasks throughput (11).

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