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비쥬얼 롭을 사용한 다수표적 탐색의 수행도 예측*

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Predicting Human Performance of Multiple-Target Search Using a Visual Lobe*

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ABSTRACT

This study is concerned with predicting human search performance using a visual lobe. The most previous studies on human performance in visual search have been limited to a single-target search. This study extended the visual search research to multiple-target search including targets of different types as well as targets of same types. A model for predicting visual search performance was proposed and the model was validated by human search data. Additionally, this study found that human subjects always did not use a constant ratio of the whole visual lobe size for each type of targets in visual search process. The more conspicuous the target is, the more ratio of the whole visual lobe size human subjects use. The model that can predict human performance in multiple-target search may facilitate visual inspection plan in manufacturing.

Keyword: Visual lobe, Visual search, Human performance, Multiple targets

1. Introduction

Human visual search has been studied in many different visual environments and from many different perspectives, perhaps because visual search is a basic perceptual/cognitive component of many human tasks. The extended visual search tasks, a topic of this study, mainly occur in practical work domains. The research on extended visual search has been initially concerned with locating air or surfaces targets such as air-to-ground target detection and ground-to-air aircraft detection(Akerman III and Kinzly, 1979; Greening, 1976). The application area was enlarged into visual inspection in a manufacturing environment(Drury, 1975), search of medical images(Nodine and Kundel, 1987), and visual inspection for aircraft maintenance(Drury, 1997).

Human performance models for extended visual search have been proposed by many studies and their validity has been also measured empirically. The authors typically have postulated the exponential time dependence for the cumulative probability of detection in visual search for a target, differently from studies of the attentional aspects of visual search. However, these

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models were primarily search models for a single target. It was not until the quite recently that models for performance in multiple−target search were developed (Drury and Hong, 2000; Harris, 1999). Their models were comparatively general models to describe human performance in multiple−target search for the same target type and included single−target search as a specific case. However, the models require more generalization before being universally applicable, first by extending the models to different targets type. There have been few empirical studies associated with multiple−target search with different types.

The current study first proposes a human performance prediction model for multiple−target search, detecting multiple targets of the same type or different type in a search filed. The model is an extension of the prediction model for a single−target search that is based on the relationship between human search performance and visual lobe size (Morawski et al., 1980). The model describes visual search performance in locating all targets in a search field, not just the first target. Before testing the predictions of multiple−target search performance model, an experiment was performed to ascertain if visual lobe size is a good predictor of search performance in extended visual search. Human performance in a single−target search was compared with the visual lobe size under five different target conditions. After that, the prediction model for multiple−target search was tested in search fields with target sets, composed of multiple targets of the same type or different types.

2. Prediction models of search performance

2.1 Model for single−target search

In visual search tasks for an extended search field, an observer uses a sequence of fixations to find targets. Typically, mathematical modeling of visual search per−formance describes a sequence of fixations. A model for single−target search was represented by the random variable, $X \sim EXP(\lambda)$, that is the time to locate a target in a search field. The cumulative detection probability was shown in equation 1.

$$Pr(X \leq t) = F(t) = 1 - Exp(-\lambda t) \quad (1)$$

where λ was a search rate and mean search time was $1/\lambda$. Morawski, Drury and Karwan [17] described the search rate, using parameters such as the number of fixations (M), search field size (A), visual lobe area (a), the probability of target detection in a fixation (p'), and average fixation duration (t_m).

$$\lambda = p'a/(At_m) \quad (2)$$

In the equation (1), the target type is an influential factor in determining the value of λ, because the target conspicuity in its background determines the two parameters (p' and a). The other parameters (A, t_m) are constant values.

The “p'” and “a” are determined by the measure−ment of visual lobe. The visual lobe is a useful concept that defines peripheral sensitivity for particular target and background characteristics and represents target detection probability as a function of distance from the center of fixation (Courtney, 1984; Courtney and Guan 1998; Baveja et al., 1996). The visual lobe has been defined by different terminologies according to different researchers; visibility area (Engel, 1977; Jacobs, 1986), and control span (Bertera and Rayner, 2000; Pomplun et al., 2001).

To measure visual lobe, participants are given search fields in a short time (~200ms to 250ms), because human observers may move their eye fixation, being exposed in longer time. Although the visual lobe is measured in a given short time, real fixation times in extended visual search are changeable. The whole area of visual lobe may also not effective in extended visual search. Therefore, many studies have assumed useful visual lobe as a part of the overall visual lobe. Typically, useful visual lobe has been assumed as a 50% visual lobe, the area over which the probability of target detection is above 50% (Courtney and Guan, 1998). The 50% visual lobe used to be applied to search performance modeling.

The shape of the area covered in a fixation is typically elliptical with longer horizon length in a search field with uniform density. However, if a search field has higher density in horizon, the shape can be assumed as a circle.

Even some studies have assumed a rectangular area in order to simplify the calculation of visual lobe (Baveja et al., 1996). Figure 1 shows a visual lobe with a circle shape assumed in this study and 50% visual lobe.

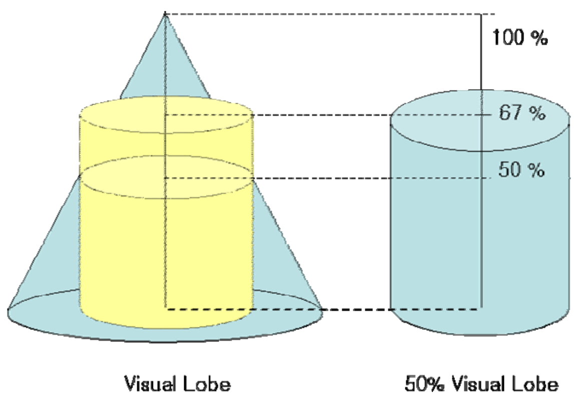

Figure 1. A visual lobe and a useful visual lobe

2.2 Model for multiple-target search

The time to locate each target of n different target types can be represented by the random variable, $X_i \sim EXP(\lambda_i)$, where i = 1, 2, 3, …n and $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \cdots \neq \lambda_n$. If multiple different targets are embedded in a search field and observers have to find all the targets, we first have to consider the joint distribution of the set of exponential random variables (X_1, X_2 X_3 …X_n) and a sampling order from the joint distribution. This is because observers can only find targets sequentially from the set of multiple targets.

Let Y_1, Y_2, Y_3, …Y_k …Y_n be random variables obtained by permuting the set X = {X_1, X_2, X_3, …X_n} into increasing order. That is $Y_1 < Y_2 < Y_3 < \cdots Y_n$. The random variable Y_k is a random variable that represents the time to locate a target kth from multiple targets and is called the k^{th}−order statistic.

Expressing the relationship between Y_1 and the set X = {X_1, X_2, X_3, … X_n},

$$Y_1 = \min\{X_1, X_2, X_3, \cdots X_n\} \quad (3)$$

Y_2 is a random variable that represents the time to locate a target among the remaining targets in the search field after one target is located. Therefore,

$$Y_2 = \min\{X_1, X_2, X_3, \cdots X_n \mid Y_1\} \quad (4)$$

The time to locate a target kth among multiple targets is

$$Y_k = \min\{X_1, X_2, X_3, \cdots X_n \mid Y_1, Y_2, Y_3, \cdots Y_{k-1}\} \quad (5)$$

We have to present how the random variables, Y_1, Y_2, Y_3, …Y_k …Y_n, are distributed with what parameters. Let us first consider a search field with three targets of different types, with $X_i \sim EXP(\lambda_i)$, where i = 1, 2, 3. The random variable Y_1 can be easily modeled as a Hypo−exponential distribution with a parameter, because the minimum of independent exponential random variables has a Hypo−exponential distribution with parameter w_1 equal to the sum of the λs of the separate exponential random variables (Trevidi, 1982).

$$Y_1 \sim HYPO(w_1) = HYPO(\lambda_1 + \lambda_2 + \lambda_3) \quad (6)$$

The random variable, Y_2, can be modeled as a Hypo−exponential distribution with two parameters (with two phases).

$$Y_2 \sim HYPO(w_1, w_2), \quad (7)$$

where $w_1 = \sum_{i=1}^{3} \lambda_i$ and $w_2 = \sum_{i=1}^{3} \frac{\lambda_i}{w_1}(w_1 - \lambda_i)$.

In the same way, the random variable, Y_3, can be also represented by a Hypo−exponential distribution with three parameters (with three phases).

Finally, the search rate for the third target is found by summing up the search rates of the three cases, weighted by the probability of their occurrence. The random variable Y_3, has a Hypo−exponential distribution with the following parameters.

$$Y_3 \sim HYPO(w_1, w_2, w_3), \quad (8)$$

where $w_1 = \sum_{i=1}^{3} \lambda_i, \quad w_2 = \sum_{i=1}^{3} \frac{\lambda_i}{w_1}(w_1 - \lambda_i),$

$$w_3 = \sum_{i=1}^{3} \sum_{j=1}^{3} \frac{\lambda_i}{w_1} \frac{\lambda_j}{w_1 - \lambda_i}(w_1 - \lambda_k),$$

$$i \neq j \neq k, \quad i, j, k: 1, 2, 3, \ldots n.$$

Until now, we have shown that the time to locate each target among multiple targets of different types is hypo-exponentially distributed. However, search performance models have been typically defined by their cumulative distribution function; the relationship between the cumulative probability of locating each target and search time for each target. As an example, if three targets of different types ($\lambda_1=0.05$, $\lambda_2=0.08$, $\lambda_3=0.10$) are embedded in a search field, the search performance models are presented as follows.

$$Y_1 \sim Hypo(0.230),$$
$$Pr(Y_1 \leq t) = F_{3,1}(t) = 1 - Exp(-0.230t) \tag{9}$$

$$Y_2 \sim Hypo(0.230,\ 0.148),$$
$$Pr(Y_2 \leq t) = F_{3,2}(t) = 1 + 1.8Exp(-0.230t) - 2.8Exp(-0.148t) \tag{10}$$

$$Y_3 \sim Hypo(0.230,\ 0.148,\ 0.069),$$
$$Pr(Y_3 \leq t) = F_{3,3}(t) = 1-0.77Exp(-0.230t) + 2.45Exp(-0.148t) - 2.68Exp(-0.069t) \tag{11}$$

3. Experiments

3.1 Tasks

To test the validity of the proposed search performance models, two experiments were performed. The first experiment measured the probability of target detection in a fixation, i.e. the visual lobe. This experiment was run for each five different targets (T, Y, A, =, ?). The second experiment, using the same participants, measured human performance in visual search for a extended search field. Visual search fields included different target sets according to conditions such as different type targets, the same type targets and single target. Participants searched until being informed that all targets have been found. Before the main tasks, participants were given training in search using the same materials as the main experiment, to ensure that performance has reached a steady state before the main experiment. The training session was comprised of 40 trials with a single target per field.

3.2 Participants and materials

Participants did not have previous experience in this search task, nor any knowledge of theoretical models of visual search strategies. The experiments were performed on a personal computer equipped with a keyboard, monitor and mouse. Each search field was generated by a Visual Basic program and presented to the participants on a color monitor, measuring 150 by 150mm and located approximately 500mm from the participants' eyes. Except for field size, visual search fields for two experiments were identical, consisting of the following background characters: !, @, #, $, %, [,], &, (,), {, }. Density of the search field was 0.7, which means that 70% of the possible character positions were filled with the remainder being blank. The main purpose of this experiment was to investigate search performance in extended visual search, and compare it with search models based on visual lobe. Full height of characters was 3.5mm and full width 2.5mm. From the viewing distance of 500mm, characters subtended a visual angle of 24.1min by 17.3min.

For visual lobe measurement, the size of the search field was 70 × 75mm (11 × 21 characters). In order to fix the subjects' eye gaze on the center of the search field, participants were given a premask, which had a cross in the center of the search field. Participants pressed the space bar for a trial. Participants tried to locate a target around their fixed gaze point in the given presentation time (250ms); a time small enough to prevent multiple fixations. After the presentation time, participants saw a postmask whose purpose was to overwrite the visual icon of the search field while still giving subjects exact locations for possible targets. Participants then clicked on the position where they located a target in the search field. Targets occurred randomly on 25 (5 × 5) positions in each trial. Each subject completed 300 trials for each target. Therefore, a target appeared ~12 times in each possible location (300 trials/25 positions = ~12). Figure 2 shows the possible positions that a target could appear.

For the search experiment, a larger search field (160× 180mm; 25 × 50 characters) was given and targets were randomly generated on the search field (see Figure 3). Participants searched until all targets were found. When participants located a target on the search field, they clicked on the target using the left mouse button. When the mouse button was clicked, the target disappeared from the search field and subjects continued to search for subsequent targets. Participants conducted 30 trials in each condition.

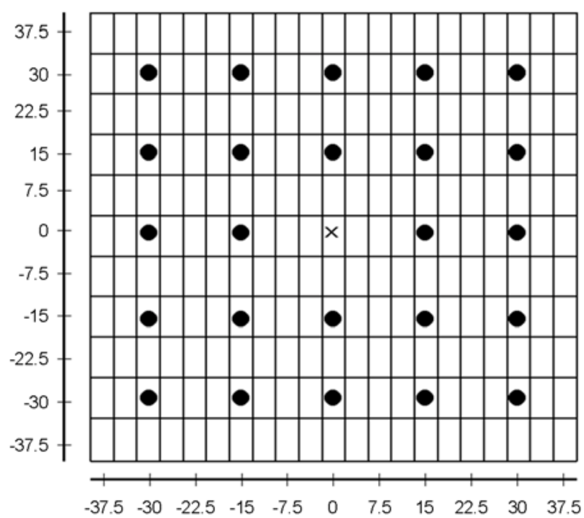

Figure 2. Possible target positions in the search field for the visual lobe measurement experiment

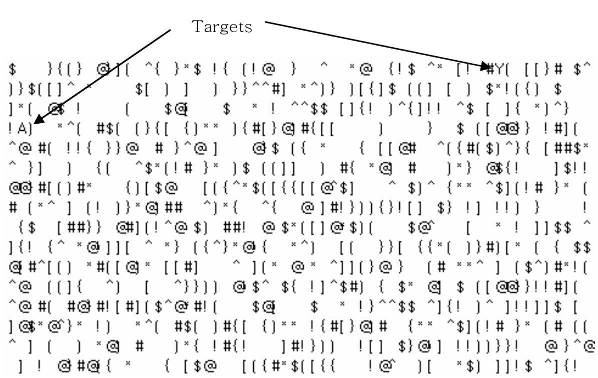

Figure 3. Part of a search field for the search time measurement experiment(This shows 16×50 character positions where the actual field was 25×50 positions)

3.3 Experimental design

The visual lobe measurement experiment was conducted for each type of targets(T, Y, A, =, ?). Each participant completed 300 trials for each target. On the other hand, performance in extended visual search was measured under ten conditions. Five conditions corresponded to single-target search for each of the five targets alone (T, Y, A, =, ?). Four conditions were two-target searches. Each condition was determined by a combination of two targets out of five possible targets, following the visual lobe measurement experiment. Three conditions, ({T, Y}, {A, T}, {A, =}), were the cases that target features differed but lobe sizes were differed, as in a typical search task with multiple targets of different types. The other one, {T, T}, was two identical targets so that their visual lobe sizes were equal. This last target set, was added to validate that the proposed performance models would describe even human performance for multiple targets of the same type. The final condition, {A, T, Y}, was a visual search field including three targets whose features differed and their visual lobe sizes also differed. Each subject conducted 30 visual search trials in each condition. Search time for each target was measured.

4. Results

4.1 Analysis of target conspicuity

A visual lobe of each target(A, =, Y, T, ?) was obtained in order to measure the conspicuity of each target in the same search field using background characters(!, @, #, $, %, [, &,], (,), {, }). The visual lobe was assumed as a corn which consists of a height of target detection probability and a circle of target detectable area. An AVOVA was performed on visual lobe size(bottom area of a corn) of each target. The visual lobe size of each target were significantly different according to participants($F(9, 49)=5.85$, $p<0.001$) and target types(($F(4, 49)=6.31$, $p=0.001$)(see Figure 4).

4.2 Relationship of visual lobe to single-target search performance

As noted earlier, lobe size is inversely proportional to visual search time. The measured lobe sizes in this experiment were also inversely proportional to mean search times for the single-target search condition. A linear regression equation with significant linear relation-ship($R^2=0.954$) was obtained as in Figure 5. Mean search time = −12.6346 + 72575.7 × (A reciprocal of visual lobe size).

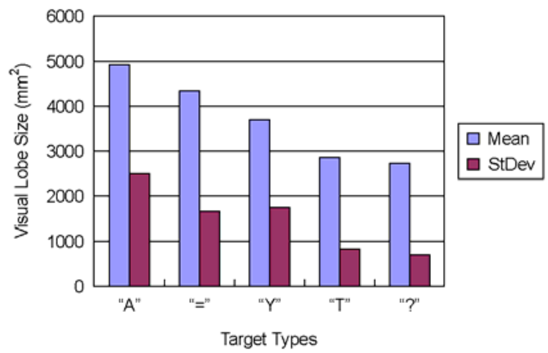

Figure 4. Mean and standard deviation of visual lobe size

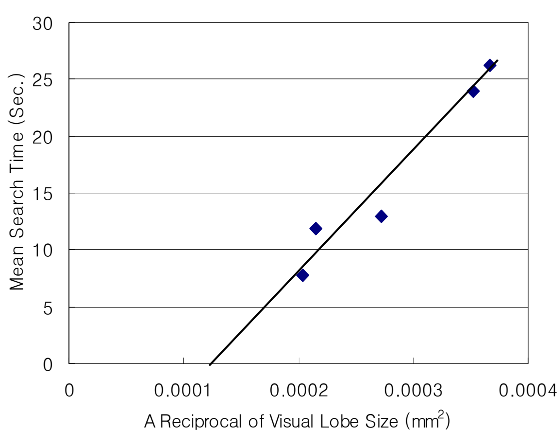

Figure 5. Relationship between visual lobe size and single−target search performance

4.3 Prediction of single target search performance

Although human performance in single−target search has close relationship with visual lobe size, we wondered if prediction model based on visual lobe was fitted to human search time. However, when typical 50% visual lobes were applied to 5 single−target searches, the prediction of the model was not well fitted to real search performance.

$$\bar{t} = 1/\lambda = \frac{At_m}{p'a}, \qquad \therefore \quad \bar{t} = \frac{k}{a}$$

where A = 28,800mm^2, t_m = 300ms, including a fixation time and saccade time and a and p' were determined the conspicuity of each target (A, =, Y, T, ?). Whilst participants found some targets (i.e. A, =, Y) earlier than even search time that the prediction model predicted, participants found targets (T, ?) later than the predictions of the model. Paired T test on mean difference showed significant mean difference ($t(4) = -0.50$, p=0.641).

We thus need to explore alternatives to the obvious assertion that the useful visual lobe in extended visual search is based on 50% visual lobe for all types of targets. The representative useful visual lobes for five targets were obtained in Table 1 by visual lobe simulation for each target, comparing human search times and predicted search times based on alternative useful visual lobes.

Table 1. Representative visual lobe used in an extended visual search

Target types	Cutting probability	Average probability	Coverage (mm^2)
A	30%	0.53	2140
=	42%	0.64	1516
Y	42%	0.64	1197
T	57%	0.72	503
?	57%	0.72	483

* Average Probability: mean probability of target detection in a useful visual lobe
Coverage: coverage of a useful visual lobe (mm^2)

4.4 Prediction of multiple−target search performance

We wondered if multiple−target search performance could be predicted by the proposed prediction model for multiple targets, when representative useful visual lobes are determined as in above Section C. Predicted mean search times in multiple−target search were determined, as shown in Table 2.

Human mean search time in multiple−target search was measured by geometric mean as in single−target search. Times that targets were found in 30 trials by each participant were categorized by the order that targets were found. A geometric mean search time (GMST) was obtained within each group. The obtained GMSTs by 10 participants were averaged for each target type as shown in Figure 6. Paired T−test on the mean difference between predicted search times and human search times did not show significant difference

($t(10) = -3.32$, $p=0.008$)

Table 2. Parameters Used in the Prediction Model for Multiple-target Search

Target set	Parameters (a, p')	$\lambda_1, \lambda_2, \lambda_3$	Predicted MST(s)
{T, T}	T:(a = 503, p' = 0.72),	$\lambda_1 = 24.0$	F : 12.0.
	T:(a = 503, p' = 0.72)	$\lambda_2 = 24.0$	S : 24.0.
{A, =}	A:(a = 2140, p' = 0.53),	$\lambda_1 = 7.8$	F : 4.7.
	=:(a = 1516, p' = 0.64)	$\lambda_2 = 11.9$	S : 9.0.
{A, T}	A:(a = 2140, p' = 0.53),	$\lambda_1 = 7.8$	F : 5.9.
	T:(a = 503, p' = 0.72)	$\lambda_2 = 24.0$	S : 9.3.
{T, Y}	T:(a = 503, p' = 0.72),	$\lambda_1 = 24.0$	F : 8.4
	Y:(a = 1197, p' = 0.72)	$\lambda_2 = 13.0$	S : 15.5
{A, T, Y}	A:(a = 2140, p' = 0.53),	$\lambda_1 = 7.8$	F : 4.1.
	T:(a = 503, p' = 0.72)	$\lambda_2 = 24.0$	S : 10.8.
	Y:(a = 1197, p' = 0.64)	$\lambda_3 = 13.0$	T : 26.5.

* Parameters(tm, A) : t_m = 300ms, A = 28800mm^2,
Predicted MST: predicted mean search time

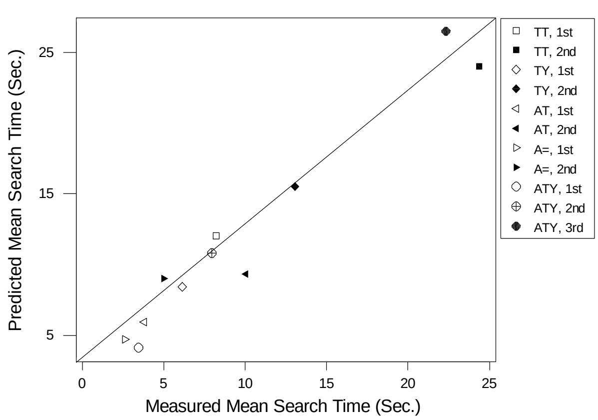

Figure 6. Prediction of multiple-target search performance

5. Discussion and conclusions

Human performance model for multiple-target search was proposed in this paper. This model is an extension to a single-target search model based on visual lobe and a general performance prediction model for multiple targets of different types as well as a single target and multiple targets of the same types. The model was represented as a hypo-exponential distribution, a family of exponential distribution.

Before validating search performance models for multiple-target search, human performance in single-target search was compared with single-target search model for each of five targets individually. Human search data for each target did not always fit to the search model, when a typical useful visual lobe(50% visual lobe) was used as a parameter. The model predicted longer search times than human search time for some targets(i.e. A =, Y), but the predictions for the other targets(T, ?) were shorter than human search times. However, there seemed to be a systematic change with target conspicuity. Whereas the targets with the larger visual lobe(highly conspicuous targets) led human observers to use even longer inter-fixation distance during visual search than that predicted by a typical visual lobe, the targets with smaller visual lobes(low conspicuity targets) led to even shorter inter-fixation distances than the typical inter-fixation distances. This may imply that a human observer's confidence regarding target detectability was a factor in determining inter-fixation distance(saccade movements) during visual search. Similarly, the relationship between an observer's confidence and inter-fixation distance was pointed out in our earlier study of multiple-target search for the same type targets(Hong and Drury, 2002). Human search typically begins with an orientation(or filter) scan, and then proceeds with a more detailed scan. Even if the initial orientation scan provides relatively poor discrimination between target and non-target features, the scan appears to be undertaken with a longer inter-fixation distance to reduce the observer's search time. On the other hand, a more detailed scan would be performed with a shorter inter-fixation distance. That is, in the initial scan, human observers would have more confidence in finding a target than in the subsequent scans. In the former case, the observers' confidence is raised by the target conspicuity and the latter by the order of scans.

In order to the predictability of proposed model for multiple-target search, useful visual lobes for each of five targets obtained from single-target search experi-ment were applied to the multiple-target search model. The differences between predicted search times and real search times were not statistically significant. This implies that the visual lobe is the dominant factor in visual search performance, rather than specific target features. However, the impact of target features on search performance may be in fact implicit in the visual lobe formulation. One of further research may be to predict visual lobe, considering relationship between target features and background features.

Courtney and Guan(1998) pointed out that "simulation using lobe area is a useful approach to studying practical problems and may provide insights that increase our knowledge of the visual search process and improve performance." However, a simulation is necessarily annexed to some assumptions. Real eye fixation times in a visual search process are various according to many situation factors. In this study, however, the tm (average duration time including saccade movement time) was used and was fixed to 300ms. Although this value is a little changed, the relationship between target conspicuity and useful visual lobe is still proved. Useful visual lobe also is changeable in a search process, but using a representative useful visual lobe is meaningful in presenting characteristics of the visual search field as a representative value.

Multiple-target search performance model that was suggested in this paper can be applied to various visual search tasks such as rescue activities and visual inspection activities in manufacturing. For an example, visual inspection for traditional quality control in manufacturing is to locate a critical defect to reject the product, while visual inspection for process control is to locate all defects as far as possible. Such a trend may increase the need of human performance model for multiple-target search. The proposed model may facilitate visual inspection plan for process control in manufacturing.

References

Akerman III, A. and Kinzly, R. E. "Predicting aircraft detectability," *Human Factors*, vol. 21, no. 3, pp. 277-291, 1979.

Baveja, A., Drury, C. G., Karwan, M. H. and Malon, D. M., "Derivation and test of an optimum overlapping lobes model of visual search," *IEEE Transactions on Systems, Man, Cybernetics*, vol. 26 no. 1, pp. 161-168, 1996.

Bertera, J. H. and Rayner, K., "Eye movements and the span of the effective stimulus in visual search," *Perception and Psychophysics*, vol. 62, no. 3, pp 576-585, 2000.

Courtney, A. J. and Guan, L., "Assessing search performance with a simulation model," *Human factors and Ergonomics in manufacturing*, vol. 8 no. 3, pp 251-263, 1998.

Courtney, A. J., "A search task to assess visual lobe size," *Human Factors*, vol. 26, pp 289-298, 1984.

Drury, C. G., "Inspection of sheet material - Model and data," *Human Factors*, vol. 17, no. 3, pp 257-265, 1975.

Drury, C. G. and Hong, S.-K., "Generalizing from signal target search to multiple target search," *Theoretical Issues in Ergonomics Science*, vol. 1, no. 4, pp 234-344, 2000.

Drury, C. G., Spencer, F. W. and Schurman, D., "Measuring human detection performance in aircraft visual inspection," *Proceedings of the Human Factors Society 41st Annual Meeting*, Albuquerque, NM, pp 304-308, 1997.

Engel, F. L., "Visual conspicuity, visual search and fixation tendencies of the eye," *Vision Research*, vol. 17, pp 95-108, 1977.

Greening, C. P. "Mathematical modeling of air-to-ground target acquisition," *Human Factors*, vol. 18, no. 2, pp 111-148, 1976.

Harris, J. M., "Models of visual search performance," Unpublished Ph. D. dissertation, Clemson University, 1999.

Hong, S.-K. and Drury, C. G., "Sensitivity and validity of visual search models for multiple targets," *Theoretical Issues in Ergonomics Science*, vol. 3, no. 1, pp 85-110, 2002.

Jacobs, A. M., "Eye-movement control in visual search: How direct is visual span control?" *Perception and Psychophysics*, vol. 39, no. 1, pp 47-58, 1986.

Morawski, T. B., Drury, C. G. and Karwan, M. H.,"Predicting search performance for multiple targets," *Human Factors*, vol. 22, pp 707-718, 1980.

Nodine, C. F. and Kundel, H. L. "Using eye movements to study visual search and to improve tumor detection," Radio Graphics vol. 7, pp 1241-1250, 1987.

Pomplun, M., Reingold, E. M. and Shen, J., "Investigating the visual span in comparative search: The effects of task difficulty and divided attention," *Cognition*, vol. 81, pp 57-67, 2001.

Trevidi, K. S., "Probability and statistics with reliability, queuing and computer science applications," Prentice Hall Inc. NJ, 1982.

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