Journal of Experimental Psychology:
Human Perception and Performance
1988, Vol. 14, No. 4, 591-600

0096-1523/88/$00.75

Visual Selection From Multielement Displays: Measuring and Modeling Effects of Exposure Duration

Hitomi Shibuya
Kyoto University,
Kyoto, Japan

Claus Bundesen
Copenhagen University,
Copenhagen, Denmark

In a partial-report experiment, subjects reported the digits from a circular array of digits and letters terminated by a pattern mask. Individual frequency distributions of the number of correctly reported digits were analyzed as functions of number of digits (2, 4, or 6) and number of letters (0, 2, 4, 6, or 8) at nine exposure durations ranging from 10 to 200 ms. The distributions (hundreds of data points per subject) were accurately predicted by a four-parameter *fixed-capacity independent race model* that assumes exponentially distributed processing times, limitations in both processing capacity and storage capacity, and time-invariant selectivity. Estimated from the data, processing capacity C was 45 items/s, selectivity α (ratio between the amount of processing capacity devoted to a distractor and the amount devoted to a target) was 0.48, short-term storage capacity K was 3.5 items, and the longest ineffective exposure duration t_0 was 18 ms.

In the partial-report paradigm, the subject is instructed to respond to a briefly exposed visual display showing a mixture of targets (e.g., digits) and distractors (e.g., letters) by reporting as many targets as possible while ignoring the distractors. Bundesen, Pedersen, and Larsen (1984) and Bundesen, Shibuya, and Larsen (1985) studied performance in this paradigm as a function of number of targets, number of distractors, and selection criterion (e.g., color or alphanumeric class). Exposure time was kept constant, pre- and postfields were dark, and the subject was informed about the selection criterion before the stimulus was presented. Under these conditions, variations in the number of correctly reported targets were accurately described by a Luce (1959) choice model developed for partial report. The model related performance to the numbers of targets (T) and distractors (D) in the stimulus, and it provided a measure of efficiency of selection (the efficiency of selecting targets rather than distractors) that was independent of T and D.

In this article, we investigate performance in the partial-report paradigm as a function of exposure duration by using a stimulus display terminated by a pattern mask. After the presentation of the experiment, we develop a model belonging to a class of "race models" (Bundesen, 1987), in which the selection process is viewed as a race between items in the stimulus display toward a certain state so that the first items reaching this state are the ones selected. The model explains our data by assuming that efficiency of visual selection (the efficiency of selecting targets rather than distractors) is independent of exposure duration. The present model encompasses our previous results (Bundesen et al., 1984, 1985) because the choice model for partial report can be derived from the race model (see Bundesen, 1987).

We wish to thank Toshio Inui for useful suggestions concerning the ideas developed in this article.

Correspondence concerning this article should be addressed to Claus Bundesen, Psychological Laboratory, Copenhagen University, Njalsgade 90, DK-2300 Copenhagen S., Denmark.

Method

The task was to report the digits from a circular array of digits and letters terminated by a pattern mask. The number of correctly reported digits was analyzed as a function of number of digits (2, 4, or 6), number of letters (0, 2, 4, 6, or 8), and exposure duration (10–200 ms).

Subjects

Two Danish students of engineering served as subjects. They were paid by the hour. Subject MP was a 23-year-old male with normal visual acuity. Subject HV was a 19-year-old female with corrected-to-normal visual acuity. Both subjects were accustomed to using computer-terminal keyboards but naive with respect to the purpose of the experiment.

Displays

Stimulus. Every stimulus display showed a number of characters (digits and capital letters) positioned around the perimeter of an imaginary circle centered on fixation. Each of the characters was positioned at either 1 o'clock, 2 o'clock, . . . , or 12 o'clock, in such a way that no position was occupied by more than one character. Under the experimental viewing conditions, a single character subtended a visual angle of about 0.4° vertically and 0.3° horizontally. The angular distance from the center of the character to the fixation point was 1.84°, and the center-to-center distance between characters in adjacent positions was 0.95°.

Let T be the number of targets (digits) in a display and D the number of distractors (letters). T was 2, 4, or 6. When T was 2, D was 0, 2, 4, 6, or 8. When T was 4, D was 0, 2, 4, or 6. When T was 6, D was 0, 2, or 4. In each display, the spatial distribution of the $T + D$ items over the 12 positions was random. Identity of individual digits was determined by drawing at random, with replacement, from a set of nine digits (excluding *0*). Identity of individual letters was determined by drawing at random, with replacement, from a set of 20 consonants (excluding *Y*).

Mask. The masking display showed 12 identical patterns, one in each of the 12 possible positions for stimulus characters. Each pattern was equal in size to a stimulus character; it consisted of a rectangle equal in height and width to an *H*, an *O* inscribed in the rectangle, an *X* forming the diagonals of the rectangle, and a cross dividing the rectangle into four identical rectangles.

Apparatus and Procedure

The subject was seated in front of a computer-driven cathode ray screen (Tektronix 604 Monitor equipped with P-31 fast-decay phosphor) at a viewing distance of 1.2 m in a semidarkened room. Each stimulus character covered about 0.8 cm × 0.6 cm on the screen. The characters were displayed by periodic intensifications at a rate of 100 Hz, each with a luminous directional energy of approximately 1 cdμs/cm (cf. Sperling, 1971); the background luminance of the screen was about 0.3 cd/m^2.

A fixation cross was presented at the center of the screen when the system was ready for a trial. When adequately fixated, the subject pressed a key to produce an immediate exposure of the stimulus display. Exposure duration was 10, 20, 30, 40, 50, 70, 100, 150, or 200 ms. When stimulus exposure terminated, the mask was exposed for a period of 500 ms.

The task was to report as many targets (digit tokens) as possible from the stimulus display and to ignore the distractors (letters). The instruction specified that a digit (token) should be reported if, and only if, the subject was "fairly certain" that it was correctly identified. The subject typed his or her report on a keyboard connected to the computer by first pressing the numeric keys corresponding to the digits to be reported—in free order—and then pressing a return key. When the return key was pressed, the reported digits were listed at the bottom of the screen, and the subject either confirmed the report by pressing one key or (if typing errors were found) corrected the report for typing errors by pressing another key and typing the corrected report. On the average, a trial took about 8 s.

Design

All variables were manipulated within subjects, and all randomizations were done independently for the 2 subjects. Either subject served in 6,480 experimental trials grouped into 60 successive blocks of 108 trials, one with each of the 108 combinations of the experimental variables (12 combinations of *T* and *D* by 9 levels of exposure duration). Ordering of trials within blocks was random. Each block was administered as two subblocks of 54 trials, and either subblock was preceded by a single practice trial for warming up.

Either subject did about 12 blocks of trials per day. Each day started with 165 practice trials; on these trials, the subject was informed by the experimenter of the number of digits correctly reported.

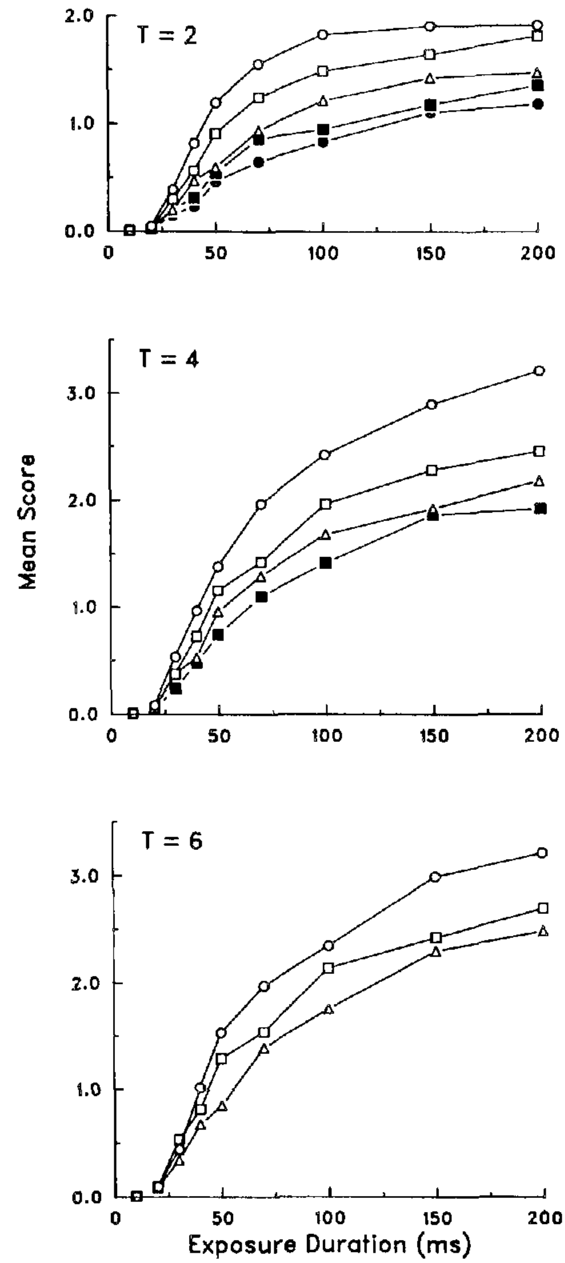

Figure 1. Group mean score (number of correctly reported targets) as a function of exposure duration with number of targets *T* and number of distractors *D* as the parameters. (*T* was 2 [top panel], 4 [middle panel], or 6 [bottom panel]. *D* was 0 [open circles], 2 [open squares], 4 [triangles], 6 [solid squares], or 8 [solid circles].)

Results

Mean Scores

For each trial, the number of correctly reported items was determined as the maximum number of nonoverlapping pairs that could be formed by pairing targets (digit tokens in the display) with responses (digit tokens in the report) in such a way that members of the same pair were identical in type. Figure 1 shows the mean number of correctly reported items (mean score) as a function of exposure duration, with number of targets *T* and number of distractors *D* as the parameters. The data are averaged across the 2 subjects. Mean score functions for individual Subjects MP and HV are shown in Figures 2 and 3, respectively. (The individual data are fitted by theoretical functions explained later in the text.) As can be seen, the data of the 2 subjects were similar in pattern.

As indicated in Figures 1–3, mean scores for exposure duration 10 ms were virtually zero, and mean scores for exposure duration 20 ms were close to zero. As exposure duration increased from 20 ms up to 200 ms, the mean score showed a steep rise followed by a gradual leveling off. Consider the rate of increase of the mean score function evaluated at short exposure durations, say, in the range from 20 ms up to 50 ms. When D was kept constant at zero, the rate of increase depended only slightly upon T. However, when T was kept constant, the rate of increase depended strongly upon D; as D increased, the mean score function became substantially less steep.

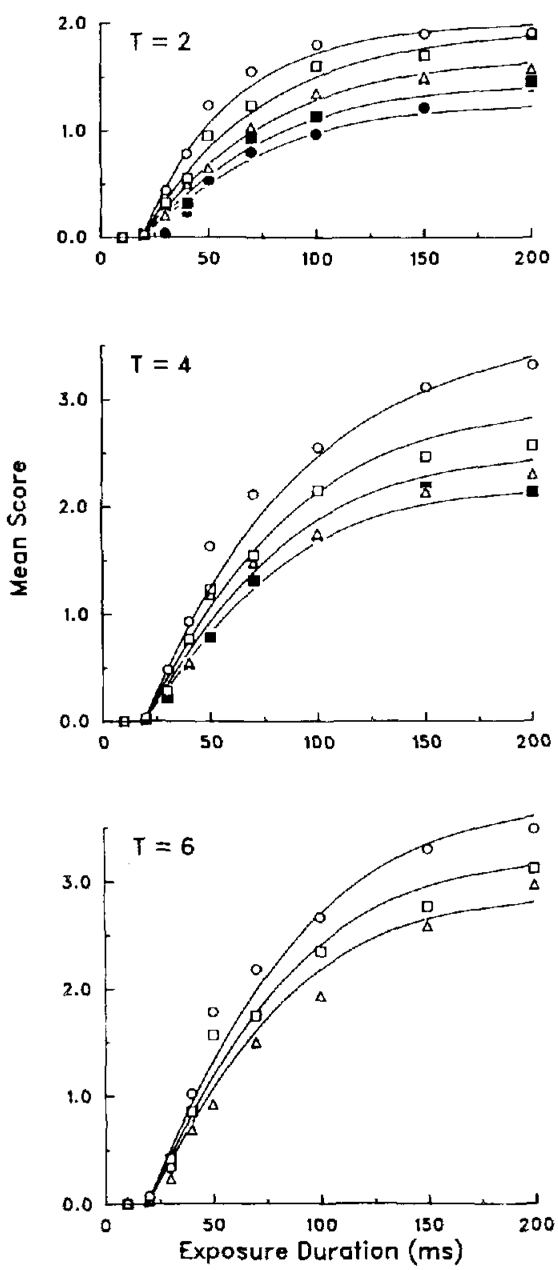

Figure 2. Mean score (number of correctly reported targets) for Subject MP as a function of exposure duration with number of targets T and number of distractors D as the parameters. (T was 2 [top panel], 4 [middle panel], or 6 [bottom panel]. D was 0 [open circles], 2 [open squares], 4 [triangles], 6 [solid squares], or 8 [solid circles]. Smooth curves represent a theoretical fit to the data by the fixed-capacity independent race model.)

Probability Correct

For both subjects, probability correct (i.e., mean score divided by T) decreased systematically with both T and D. When the total number of display elements $T + D$ was kept constant, probability correct decreased as T increased and D decreased. In other words, the probability that a given target was correctly reported was reduced by competing display elements, whether these were targets or distractors, but the reduction caused by a competing target was greater than the reduction caused by a competing distractor. This difference in effects of competing targets and competing distractors appeared at all exposure durations of 30 ms or more. For a numerical example, consider probability correct for displays with $T + D$ equal to 6. When exposure duration was 30 ms, probability correct (averaged across the 2 subjects) was .100 for $T = 2$ and $D = 4$, .094 for $T = 4$ and $D = 2$, and .074 for $T = 6$ and $D = 0$. When exposure duration was 200 ms, probability correct was .74 for $T = 2$ and $D = 4$, .62 for $T = 4$ and $D = 2$, and .53 for $T = 6$ and $D = 0$.

Effects of serial position (i.e., spatial position in the circular array) were small. For example, when exposure duration was 100 ms, probability correct for displays without distractors averaged .65, .73, .74, .60, .62, .54, .57, .68, .72, .68, .58, and .60, in that order, for target positions 1 o'clock through 12 o'clock.

Distribution of Scores

The frequency distributions of scores underlying the mean scores depicted in Figures 2 and 3 were highly systematic. Results for the 2 subjects were similar. Figure 4 shows *cumulative relative frequencies* of scores for Subject MP as functions of exposure duration: Let cumulative frequency F_j be the relative frequency of scores of j or more correctly reported targets. Each panel in Figure 4 shows F_j as a function of exposure time for a given combination of T and D, with j as the parameter. (Again the data are fitted by theoretical functions explained later in the text.) Hence, the distance in the direction of the ordinate between 1 and F_1 equals the relative frequency of scores of exactly 0, the distance between F_1 and F_2 equals the frequency of scores of exactly 1, and so on. Furthermore, for each combination of T and D, the sum of the cumulative frequency functions F_j shown in Figure 4 equals the mean score function shown in Figure 2.

The cumulative frequencies F_j depicted in Figure 4 for each combination of T and D increased systematically as functions of exposure duration. In general, cumulative frequency function F_1 showed a relatively steep rise as exposure duration exceeded some 20 ms. Function F_2 was substantially less steep than F_1. For T greater than 2, F_3 was less steep than F_2, and F_4 less steep than F_3.

Scores higher than 4 were very rare. Subject MP attained a score of 5 on 4 out of 60 trials with T:D combination 6:0, and 1 out of 60 trials with T:D combination 6:4; he never attained a score of 6. Scores for Subject HV never exceeded 4.

When D was kept constant at zero, cumulative frequency functions F_j, for $j \leq T$, showed rather little effect of T. In particular, function F_1 showed little or no effect of T. In

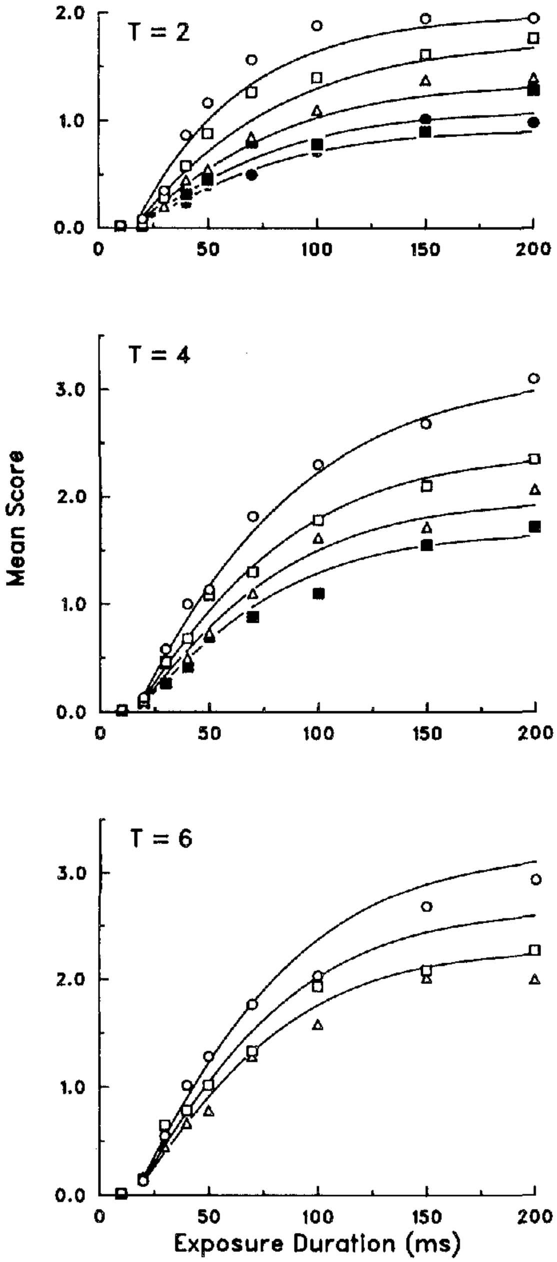

Figure 3. Mean score (number of correctly reported targets) for Subject HV as a function of exposure duration with number of targets T and number of distractors D as the parameters. (T was 2 [top panel], 4 [middle panel], or 6 [bottom panel]. D was 0 [open circles], 2 [open squares], 4 [triangles], 6 [solid squares], or 8 [solid circles]. Smooth curves represent a theoretical fit to the data by the fixed-capacity independent race model.)

contrast, when T was kept constant, the cumulative frequency functions depended strongly upon D; as D increased, the initial slope of the functions decreased.

Errors

In general, intrusion errors were rare. The mean number of erroneously reported items averaged 0.07 (SD = 0.06) for Subject MP and 0.13 (SD = 0.09) for Subject HV across the 108 combinations of T, D, and exposure duration. For comparison, the mean number of correctly reported items averaged 1.10 (SD = 0.96) for Subject MP and 0.94 (SD = 0.78) for Subject HV. Thus, the percentage of errors among the reported items was 6% for Subject MP and 12% for Subject HV. The product-moment correlation between the mean score and the mean number of erroneously reported items as functions of T, D, and exposure duration was .49 for Subject MP and .02 for Subject HV.

For displays presented at the shortest exposure duration, an unusually high proportion of the reported items was in error. From a total of 720 displays with exposure duration equal to 10 ms, Subject MP reported a total of 3 items, and 2 of these were in error. Similarly, summed over 720 trials, Subject HV reported a total of 25 items, and 13 of these were in error.

Discussion

Limited Processing Capacity

The results strongly support the hypothesis that items were sampled from the display by a process with limited capacity (cf. Sperling, 1963). For the sake of argument, suppose that items were sampled in parallel and independently, by a process with unlimited capacity. If so, the expected score for a display with T targets at a given exposure duration should equal T times the expected score for a one-target display at the same exposure duration, provided that both scores were unaffected by limitations in storage capacity. Theoretically, effects of limitations in storage capacity should be negligible for exposure durations at which the number of items sampled is close to zero. On the hypothesis of unlimited-capacity parallel processing, therefore, the initial rate of increase as the mean score function rises from zero should be proportional to T. The results went counter to this prediction.

Rather than being proportional to T, the initial rate of increase of the mean score function showed little dependence upon T when D was kept constant at zero. This finding suggests that the sampling process was approximately fixed in capacity. Moreover, when T was kept constant, the initial rate of increase of the mean score function decreased substantially with increasing D. This finding suggests that distractors in the display interfered with performance by attaching a portion of the available processing capacity.

Selectivity

The probability that a given target was correctly reported was reduced by competing display elements whether these were targets or distractors. However, the reduction caused by a competing distractor was less than the reduction caused by a competing target, and the difference in effects of competing targets and competing distractors was apparent at all exposure durations of 30 ms or more. This result suggests that allocation of processing resources was selective so that, on the average, the available processing capacity captured by a distractor was less than the capacity allocated to a target.

It is harder to determine whether selectivity was constant across exposure durations. To compare selectivity across variations in T, D, and exposure duration, we need a model with a measure for efficiency of selection that is applicable across variations in T and D and across the variations in level of performance generated by variations in exposure duration.

Limited Storage Capacity

The results suggest that performance was constrained by limitations in storage capacity in addition to limitations in processing capacity (cf. Sperling, 1967). Specifically, as argued below, it seems hard to account for the data by independent parallel or independent serial models in which items are sampled from the display as long as stimulus information is available, regardless of the number of items already sampled.

Independent Parallel Models

Suppose items were sampled from the display as long as stimulus information was available, regardless of the number of items already sampled, and suppose the items were sampled in parallel and independently in the sense that the times required to sample individual items were independent random variables. If so, and if sampling times for individual targets were identically distributed, then the number of targets sampled from a display with T targets at a given exposure duration should follow a binomial distribution for T Bernoulli

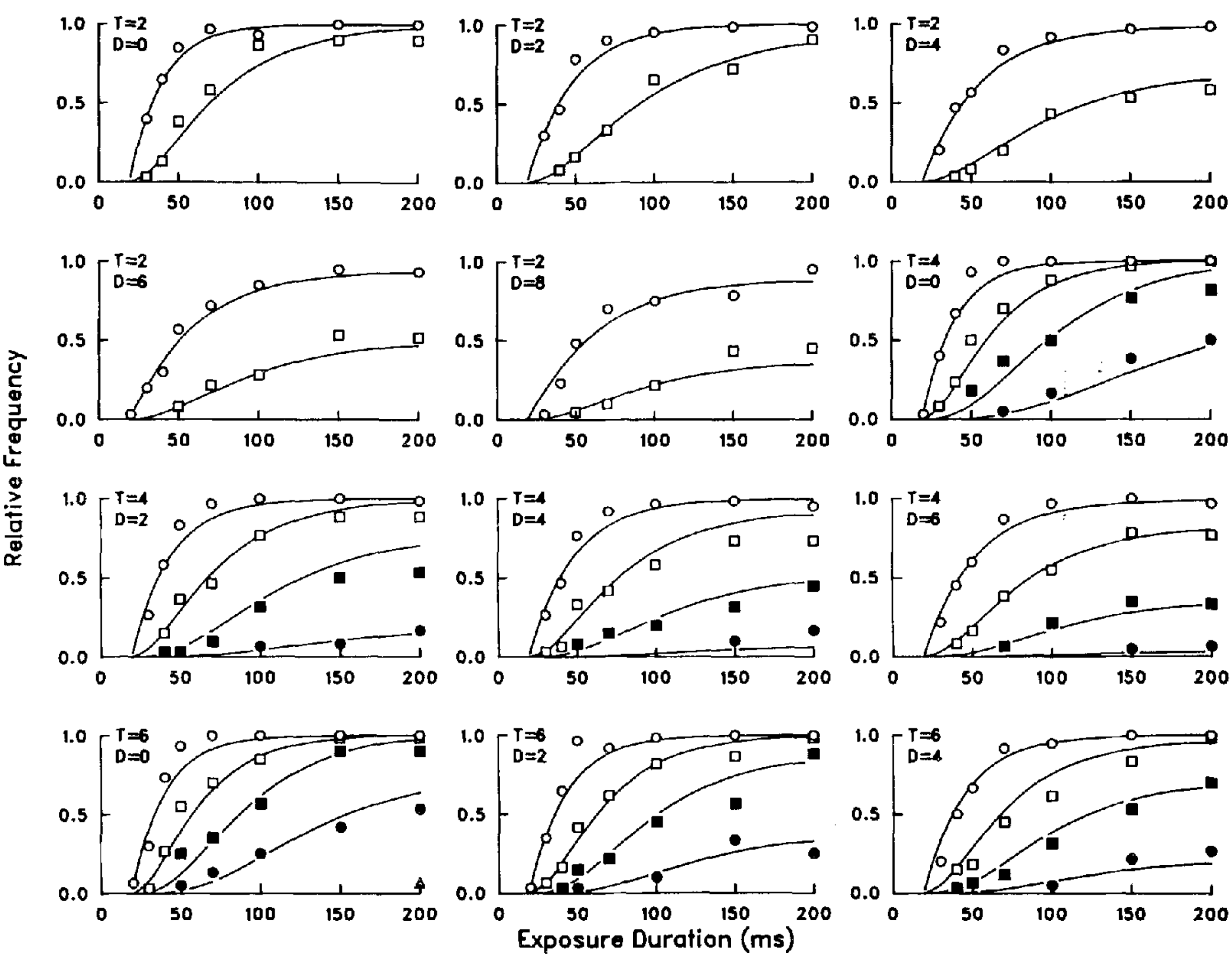

Figure 4. Relative frequency of scores of j or more (correctly reported targets) as a function of exposure duration with j, number of targets T, and number of distractors D as the parameters for Subject MP. (Parameter j varies within panels; j is 1 [open circles], 2 [open squares], 3 [solid squares], 4 [solid circles], or 5 [triangle]. T and D varies between panels; their values are indicated on the figure. Smooth curves represent a theoretical fit to the data by the fixed-capacity independent race model. For clarity, observed frequencies less than .02 are omitted from the figure.)

trials, with a certain probability p for success. However, the accumulation of scores of 3 and 4 (but not 5 or 6) items correct observed at long exposure durations for displays with six targets and few distractors violated this prediction.

Consider the results for displays with 6 targets and no distractors when exposure duration was 200 ms. The relative frequency of scores of 3 or 4 items correct was .83 for Subject MP and .75 for Subject HV. The probability of obtaining 3 or 4 successes in 6 Bernoulli trials with probability p for success on each trial is a function of p; the function may be shown to have an absolute maximum at $p = 2 - \sqrt{2}$, and the absolute maximum is approximately .59. Taken together, the deviations between the observed frequencies of .83 and .75 and the maximum theoretical probability of .59 were significant at the .001 level.

Models with fixed processing capacity. It is instructive to consider the manner in which an independent parallel model with fixed processing capacity but unlimited storage capacity would fail to account for the observed mean scores. We limit the discussion to processing of displays with T targets and zero distractors and assume that (a) regardless of T, the fixed processing capacity is evenly distributed among the T targets, and (b) once distributed on a given trial, processing capacity is not redistributed on that trial.

In the type of model we examine (exemplified by the multicomponent model of Rumelhart, 1970), the effect of processing an item for t ms with a capacity of c units should equal the effect of processing the item for ct ms with a capacity of 1 unit (cf. Bundesen, 1987). Hence, if the amount of processing capacity allocated to each individual target in a display with T targets equals $1/T$ of the amount of capacity allocated to a single target in a one-target display, then the expected contribution to the score from each individual target in a T-target display with an effective exposure duration of t ms should equal the mean score for a one-target display with an effective exposure duration of t/T ms. Therefore, the mean score for a display with T targets and an effective exposure duration of t ms should equal T times the mean score for a one-target display with an effective exposure duration of t/T ms. In symbols,

$$m_T(t) = Tm_1(t/T)$$

3

or, equivalently,

$$m_T(Tt) = Tm_1(t). \qquad (1)$$

Using Equation 1, a graph showing the theoretical mean score as a function of effective exposure duration for displays with, say, T' targets can easily be constructed from a graph showing the theoretical mean score for displays with T targets. Specifically, Equation 1 implies that

$$m_{T'}[(T'/T)t] = (T'/T)m_T(t), \qquad (2)$$

which means that the graph for T' targets is a size-scaled version of the graph for T targets where the scaling is a geometric multiplication by factor T'/T with respect to the origin of the coordinate system.

Predictions from Equation 2 are illustrated in Figure 5. The predictions shown in the upper panel were made on the assumption that the effective exposure duration equaled the duration of the stimulus exposure. The three functions graphed in the panel are, first, the observed mean score function (averaged across the 2 subjects) for displays with 2 targets (and zero distractors); second, a predicted mean score function for displays with 2 targets generated by multiplying the observed mean score function for displays with 4 targets (and zero distractors) by a factor of ½ with respect to the origin of the coordinate system; and third, a predicted mean score function for displays with 2 targets generated by multiplying the observed mean score function for displays with 6 targets (and zero distractors) by a factor of ⅓ with respect to the origin of the coordinate system.

As noted by Rumelhart (1970), "there is probably some rise time or latency associated with the onset of processing following the onset of the display" (p. 193). The predictions shown in the lower panel of Figure 5 were made on the assumption that the effective exposure time equaled the duration of the stimulus exposure minus some 18 ms. The three functions are similar to those in the upper panel except that the two predicted functions were constructed by multiplications with respect to the 18-ms point on the time axis.

The predictions from Equation 2 illustrated in Figure 5 are grossly in error, and the discrepancy cannot be remedied by

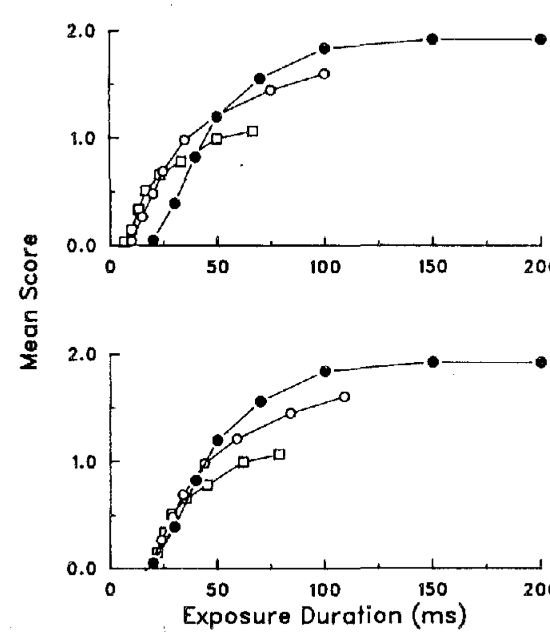

Figure 5. Group mean scores (numbers of correctly reported targets) for displays with two targets and zero distractors at various exposure durations (20–200 ms) compared with transformed group means for no-distractor displays with four and six targets, respectively. (Observed scores for two targets, transformed scores for four targets, and transformed scores for six targets are indicated by solid circles, open circles, and squares, respectively. Upper panel: transformed scores generated by geometric multiplication with respect to the origin of the coordinate system. Lower panel: transformed scores generated by geometric multiplication with respect to the 18-ms point on the time axis.)

shifting the center of geometric multiplication along the time axis. Apparently, the observed pattern of scores cannot be accommodated by independent parallel models with fixed processing capacity but unlimited storage capacity: Observed scores for displays with 6 targets were much too low in relation to scores for displays with 2 targets.

Independent Serial Models

Suppose items were sampled from the display as long as stimulus information was available, regardless of the number of items already sampled, and suppose the items were sampled in series and independently in the sense that the time required to process an item was independent of the time taken to process any previous items. If so, and if sampling times (effective processing times) for individual targets were identically distributed with probability density $f(t)$, then the time required to sample j targets from a display with T targets and zero distractors (where $T \geq j$) should be distributed with probability density $f^{*j}(t)$, that is, $f(t) * f(t) * \ldots * f(t)$ [j times], where $*$ stands for convolution. One parameter-free prediction is that the probability of sampling 5 or more targets in less than t ms should be not less than the product of the probability of sampling 2 or more targets in less than $t/2$ ms, and the probability of sampling 3 or more targets in less than $t/2$ ms. The observed distributions of scores went counter to this prediction.

Compare the results for displays with 6 targets and no distractors at exposure duration 200 ms with results for the same displays at exposure duration 100 ms. F_2(100 ms) (i.e., the relative frequency of scores of 2 or more when exposure duration was 100 ms) was .85 for Subject MP and .77 for Subject HV. F_3(100 ms) was .57 for MP and .25 for HV. Thus the product of F_2(100 ms) and F_3(100 ms) was .48 for MP and .19 for HV. However, F_5(200 ms) was only .07 for MP and zero for HV. A test of the null hypothesis that F_2(100 ms) $\times$ F_3(100 ms) = F_5(200 ms) yielded $\chi^2(1, N = 120) = 22.3$, $p < .001$, for Subject MP and $\chi^2(1) = 11.1$, $p < .001$, for Subject HV.7

A Fixed-Capacity Independent Race Model

As argued above, the results suggest that performance was constrained by limitations in both processing capacity and storage capacity. Perhaps the simplest model with such constraints is a parallel model with fixed processing capacity C (items/s) and fixed storage capacity K (items). A plausible model of this type—a fixed-capacity independent race model (cf. Bundesen, 1987)—is described and tested below. The model explains the data on the hypothesis that efficiency of visual selection (the efficiency of selecting targets rather than distractors) is independent of exposure duration.

Assumptions

At the first stage of processing, evidence is collected for each item in the stimulus display that the item is a target (i.e., satisfies the selection criterion). The strength of this evidence is (a) approximately the same for any target in the display as for any other target in the display and (b) approximately the same for any distractor in the display as for any other distractor in the display. The ratio between the strength of the evidence that an individual distractor is a target and the strength of the evidence that an individual target is a target is called α. As explained below, α serves as a measure for the efficiency of selecting targets rather than distractors.

At the second stage of processing, items are sampled (encoded) into a short-term memory store. The sampling process is limited in capacity. Specifically, on each trial a total processing capacity (sampling capacity) of C items/s is distributed over the items in the stimulus display. The amount of processing capacity allocated to an individual item is directly proportional to the strength of the evidence (provided by the first stage of processing) that the item is a target. Once distributed on a given trial, processing capacity is not redistributed on that trial.

The sampling process is activated t_1 ms after the onset of the stimulus display (provided that less than t_2 ms have elapsed after onset of the mask). During the period in which the sampling process is active, the conditional probability density that an individual item i will be sampled at a given moment of time, provided that the item has not been sampled before this moment, is a constant. This constant is identical to the amount of processing capacity allocated to item i.

The sampling process continues until either (a) the number of items sampled equals K, where K is the storage capacity of the short-term memory store, or (b) t_2 ms have elapsed after onset of the mask. The difference between displays t_1 and t_2, $t_1 - t_2$, is denoted t_0, and t_0 is a constant.

Finally, overt responses reflect the outcome of the sampling process: The number of targets correctly reported on a given trial is approximately the same as the number of targets sampled on that trial.

Formulas[1]

Let w_1 be the strength of the evidence (provided by the first stage of processing) that an individual target satisfies the selection criterion, and let w_0 be the strength of the evidence that an individual distractor satisfies the selection criterion. Then $w_0 = \alpha w_1$. For a display with T targets and D distractors, the processing capacity allocated to an individual target equals the product of the total processing capacity C and the ratio $w_1/(Tw_1 + Dw_0)$, and this product reduces to $C/(T + \alpha D)$. Similarly, the processing capacity allocated to an individual distractor becomes $\alpha C/(T + \alpha D)$.

During the period in which the sampling process is active, the conditional probability density that an individual target will be sampled at a given moment of time, provided that the target has not been sampled before this moment, is a constant equal to $C/(T + \alpha D)$. By implication, so long as the sampling process is active, the unconditional probability density $f(t)$ that the target will be sampled t ms ($t > 0$) from the beginning of the sampling period is exponential with rate parameter

[1] This section may be omitted without loss of continuity.

$C/(T + \alpha D)$; that is,

$$f(t) = \mu e^{-\mu t}, \tag{4}$$

where $\mu = C/(T + \alpha D)$. The corresponding distribution function (i.e., the probability that the target is sampled at or before time t) is denoted $F(t)$, and

$$F(t) = 1 - e^{-\mu t}. \tag{5}$$

Similarly, the unconditional probability density $g(t)$ that an individual distractor is sampled at time t is exponential with rate parameter $\alpha C/(T + \alpha D)$; that is,

$$g(t) = \alpha\mu e^{-\alpha\mu t}. \tag{6}$$

The distribution function corresponding to $g(t)$ is denoted $G(t)$, and

$$G(t) = 1 - e^{-\alpha\mu t}. \tag{7}$$

Let $\tau = x - t_0$, where x is the exposure duration of the stimulus display. If $\tau \le 0$, then no items are sampled, and the number of items correctly reported (the score) is zero. Suppose that $\tau > 0$ and consider the probability P that the number of targets sampled (= the score) equals j, where $0 \le j \le \min(T, K)$. Let m be the number of distractors sampled. P is a sum of three probabilities, P_1, P_2, and P_3. P_1 is the probability that the score equals j *and* the number of items sampled (i.e., $j + m$) is less than K. In this case, the sampling process is active for a period of τ ms. If $j = K$, P_1 is zero; otherwise,

$$P_1 = \binom{T}{j} F(\tau)^j[1 - F(\tau)]^{T-j} \times \sum_{m=0}^{\min(D,K-j-1)} \binom{D}{m} G(\tau)^m[1 - G(\tau)]^{D-m}. \tag{8}$$

P_2 is the probability that the score equals j *and* the number of items sampled equals K *and* the Kth item sampled is a target. In this case, the sampling process is active for a period of t ms, where $0 < t \le \tau$. If $j = 0$ or $j < K - D$, P_2 is zero; otherwise,

$$P_2 = \binom{T}{1}\binom{T-1}{j-1}\binom{D}{m} \times \int_0^\tau F(t)^{j-1}[1 - F(t)]^{T-j}G(t)^m[1 - G(t)]^{D-m}f(t)\,dt, \tag{9}$$

where $m = K - j$.

Finally, P_3 is the probability that the score equals j *and* the number of items sampled equals K *and* the Kth item sampled is a distractor. Again, the sampling process is active for a period of t ms where $0 < t \le \tau$. If $j = K$ or $j < K - D$, P_3 is zero; otherwise,

$$P_3 = \binom{D}{1}\binom{D-1}{m-1}\binom{T}{j} \times \int_0^\tau G(t)^{m-1}[1 - G(t)]^{D-m}F(t)^j[1 - F(t)]^{T-j}g(t)\,dt, \tag{10}$$

where $m = K - j$.

Fits

A maximum likelihood fit of the model to the observed frequency distributions of scores was computed for each of the 2 subjects (with scores 4–6 combined for $T = 6$). The data were not corrected for guessing, but data for exposure duration 10 ms were excluded from the analysis because an unusually high proportion of the reported items for this condition were in error.

The fits were computed by a program using an iterative method for searching the space of parameters. All parameters were treated as continuous; for noninteger values of K, predicted frequencies were calculated as weighted averages so that, for instance, a value of 3.74 for K was treated as a mixture of values of 3 and 4, with a probability of .74 for having K set at 4.

The maximum likelihood fits were remarkably good. The fit to the data of Subject MP is shown in Figure 4. It was obtained with C (processing capacity) at about 48.7 items/s, α (processing capacity per distractor with processing capacity per target as the unit) at about 0.40, K (storage capacity) at about 3.74 items, and t_0 (longest ineffective exposure duration) at about 19 ms. Mean scores predicted by the fit are shown in Figure 2. The predicted means accounted for 98.2% of the variance in the observed means.

The fit to the data of Subject HV was comparable to the fit to the data of Subject MP. It was obtained with C at about 41.1 items/s, α at about 0.57, K at about 3.21 items, and t_0 at about 16 ms. The mean scores predicted by the fit are shown in Figure 3. They accounted for 97.5% of the variance in the observed means.

Considering the amount and complexity of the data and the small number of model parameters, the goodness of fit between model and data is highly impressive.[2] For completeness, however, two minor discrepancies should be listed. First, on five trials with T equal to 6, Subject MP reported more than four items correct. As the model stands, scores above 4 should never be obtained with parameter K set below 4. Second, though very close to zero and hard to analyze exactly, the data for exposure duration 10 ms suggested true mean scores slightly above zero for Subject HV. As the model stands, scores above zero should never be obtained for exposure duration 10 ms when parameter t_0 is greater than 10 ms.

General Discussion

Theoretical analysis of the present experiment on the efficiency of partial report as a function of exposure duration suggested limited storage capacity, limited processing capacity, and moderate selectivity. Specifically, it appeared that items were sampled from the display by a process with limited capacity, and allocation of this capacity was selective in such

[2] A perfect fit of the model to the observed frequency distributions of scores would imply a perfect fit between predicted and observed values of any statistic definable in terms of the frequency distributions. This class of statistics is comprehensive; it includes, for example, a number of measures for degree of interitem dependence (cf. Townsend & Ashby, 1983, chap. 11).

a way that the capacity allocated to a target (a digit) was greater than the capacity allocated to a distractor (a letter). A four-parameter parallel model built on this assumption—a *fixed-capacity independent race model*—described the data in great detail. The model is simple, and estimates for the parameters were plausible. Averaged across subjects, the estimate for parameter C (processing capacity) was 45 items/s, the estimate for α (processing capacity per distractor with processing capacity per target as the unit) was 0.48, the estimate for K (storage capacity) was 3.5 items, and the estimate for t_0 (longest ineffective exposure duration) was 18 ms. Parameter α is a measure for efficiency of selection (the efficiency of selecting targets rather than distractors), and the model explained the data by assuming that α is independent of exposure duration. Reassuringly, the model encompasses our previous results (Bundesen et al., 1984, 1985) because the choice model for partial report can be derived from the race model (see Bundesen, 1987).

Related Work

Our work was inspired by data and arguments provided by Allport (1977), Broadbent (1970), Coltheart (1972), Duncan (1980, 1983, 1985), Hoffman (1978, 1979), Kahneman and Treisman (1984), Merikle (1980), Mewhort, Marchetti, Gurnsey, and Campbell (1984), Posner (1982), Rumelhart (1970), Shiffrin, Dumais, and Schneider (1981), Sperling (1960, 1963, 1967), Townsend and Ashby (1983), van der Heijden (1981), and von Wright (1968). Among these contributions, three stochastic models that are comparable in specificity to the fixed-capacity independent race model are treated below.

Bounded performance model of Townsend and Fial. In the bounded performance model developed by Townsend and Fial (cited in Townsend & Ashby, 1983, chap. 11), items (alphanumeric characters) in the stimulus display are assumed to be processed in parallel and independently in the sense that the times required to process individual items are independent random variables. Specifically, let C be the total capacity available for stimulus processing. Let effective exposure time t be the stimulus duration minus a constant t_0. And let $I(t)$ represent the quantity of stimulus information available at time t for any item i. $I(t)$ is assumed to grow as a function of effective exposure time t so that

$$I(t) = I \cdot (1 - e^{-Vt}),$$

where I and V are constants. And the probability that item i is correctly reported via nonguessing is presumed to be given by

$$P_i(t) = \min[1, a_i \cdot C \cdot I(t)/I],$$

where a_i is the attentional weight of item i and a_iC is the capacity devoted to item i.

Formally, the bounded performance model bears some similarity to the fixed-capacity independent race model, but it seems difficult to extend the bounded performance model to account for the data obtained in the present experiment. Townsend and Fial applied their model to a whole-report experiment in which display size was fixed. In an attempt to apply the model to whole-report data from the present experiment, one would like to keep constant parameters C, I, and V regardless of display size. With this constraint, the model implies that the mean score (by means of nonguessing) for a display with T targets and zero distractors is

$$\sum_{i=1}^{T} P_i(t) = \min[T, C \cdot (1 - e^{-Vt})],$$

provided that attentional weights a_i and a_j are the same for any targets i and j. Thus, at any exposure duration at which the mean score for four-target displays is less than 2, the mean score for two-target displays should be identical to the mean score for four-target displays. Moreover, at any exposure duration at which the mean score for four-target displays is greater than 2, the mean score for two-target displays should be exactly 2. These predictions seem implausible, and they were not supported by our data (cf. Figure 1).

Multicomponent model of Rumelhart. Like the bounded performance model, the multicomponent model of Rumelhart (1970) assumes that items (alphanumeric characters) in the stimulus display are processed in parallel and independently. An item completes processing if, and only if, c features of the item are extracted. Extractions of features from items in the display are assumed to be events of Poisson type with an overall intensity ν, which is constant until the offset of the display. When attention is evenly distributed among the N items in the display, features are extracted from each item at a Poisson rate of ν/N. If the stimulus is terminated by a fully effective pattern mask, ν changes to zero when the mask is presented. For briefly exposed visual displays, the number of items correctly reported is assumed to be bounded by the limited rate of feature extraction but not by limitations in storage capacity.

Implications of the multicomponent model for whole report were critically examined in a previous section of this article. With regard to partial report, Rumelhart's (1970) treatment of selection based on spatial position is formally similar to the treatment of selection (by variation in parameter α) in the fixed-capacity independent race model. However, the multicomponent model has not been developed to account for selection by criteria such as alphanumeric class.

Two-stage model of Hoffman. In the visual search model proposed by Hoffman (1978, 1979), search is a two-stage process in which a parallel evaluation of the entire stimulus display guides a slow serial processor (cf. Neisser, 1967). The parallel evaluation is preattentive and quick, but error prone. For each item, the outcome is an overall measure of the similarity between that item and the members of a prespecified set of targets (e.g., the memory set in a Sternberg-type experiment). Items are then serially transferred, in order of decreasing similarity, to the second stage of processing (consisting, e.g., in serial-exhaustive comparison against members of the memory set). The transfer mechanism is presumed to be the same as the spatial selective attention mechanism studied by Colegate, Hoffman, and Eriksen (1973). This mechanism is slow: Transfer time is assumed to be uniformly distributed between 0 and 200 ms.

The two-stage model of Hoffman was not developed for partial report, and it cannot account for our data as it stands. First, the transfer mechanism assumed in the model is much too slow. Second, as described earlier in this article, analysis of our data argued against independent serial models without explicit limitations on storage capacity. However, as is well known (see, e.g., Townsend & Ashby, 1983), it may be hard (if not impossible) to discriminate empirically between serial models and fixed-capacity parallel models, and it remains to be seen how closely an appropriate serial model, more or less similar to the two-stage model of Hoffman, could imitate the success of the independent race model in accounting for partial reports.

Methodological Note

As far as we know, cumulative relative frequency distributions of partial or whole report scores have not previously been traced as functions of exposure duration. Systematic studies of efficiency of selection as a function of exposure duration have not been found in the literature on partial report (see Coltheart, 1980, for a review), and previous investigators of whole report as a function of exposure duration have studied either mean score functions (e.g., Sperling, 1963) or serial (i.e., spatial) position curves (e.g., Sperling, 1967). Our method of analysis seems appropriate for experiments in which effects of serial position are small. When this requirement is met, cumulative frequency graphs like those shown in Figure 4 appear to provide a detailed picture of visual selection from multielement displays.

References

Allport, D. A. (1977). On knowing the meaning of words we are unable to report: The effects of visual masking. In S. Dornic (Ed.), *Attention and performance VI* (pp. 505–534). Hillsdale, NJ: Erlbaum.

Broadbent, D. E. (1970). Stimulus set and reponse set: Two kinds of selective attention. In D. I. Mostofsky (Ed.), *Attention: Contemporary theory and analysis* (pp. 51–60). New York: Appleton-Century-Crofts.

Bundesen, C. (1987). Visual attention: Race models for selection from multielement displays. *Psychological Research, 49,* 113–121.

Bundesen, C., Pedersen, L. F., & Larsen, A. (1984). Measuring efficiency of selection from briefly exposed visual displays: A model for partial report. *Journal of Experimental Psychology: Human Perception and Performance, 10,* 329–339.

Bundesen, C., Shibuya, H., & Larsen, A. (1985). Visual selection from multielement displays: A model for partial report. In M. I. Posner & O. S. M. Marin (Eds.), *Attention and Performance XI* (pp. 631–649). Hillsdale, NJ: Erlbaum.

Colegate, R. L., Hoffman, J. E., & Eriksen, C. W. (1973). Selective encoding from multielement visual displays. *Perception & Psychophysics, 14,* 217–224.

Coltheart, M. (1972). Visual information-processing. In P. C. Dodwell (Ed.), *New horizons in psychology* (Vol. 2, pp. 62–85). Harmondsworth, England: Penguin Books.

Coltheart, M. (1980). Iconic memory and visible persistence. *Perception & Psychophysics, 27,* 183–228.

Duncan, J. (1980). The locus of interference in the perception of simultaneous stimuli. *Psychological Review, 87,* 272–300.

Duncan, J. (1983). Perceptual selection based on alphanumeric class: Evidence from partial reports. *Perception & Psychophysics, 33,* 533–547.

Duncan, J. (1985). Visual search and visual attention. In M. I. Posner & O. S. M. Marin (Eds.), *Attention and performance XI* (pp. 85–105). Hillsdale, NJ: Erlbaum.

Hoffman, J. E. (1978). Search through a sequentially presented visual display. *Perception & Psychophysics, 23,* 1–11.

Hoffman, J. E. (1979). A two-stage model of visual search. *Perception & Psychophysics, 25,* 319–327.

Kahneman, D., & Treisman, A. (1984). Changing views of attention and automaticity. In R. Parasuraman & D. R. Davies (Eds.), *Varieties of attention* (pp. 29–61). New York: Academic Press.

Luce, R. D. (1959). *Individual choice behavior.* New York: Wiley.

Merikle, P. M. (1980). Selection from visual persistence by perceptual groups and category membership. *Journal of Experimental Psychology: General, 109,* 279–295.

Mewhort, D. J. K., Marchetti, F. M., Gurnsey, R., & Campbell, A. J. (1984). Information persistence: A dual-buffer model for initial visual processing. In H. Bouma & D. G. Bouwhuis (Eds.), *Attention and performance X: Control of language processes* (pp. 287–298). Hillsdale, NJ: Erlbaum.

Neisser, U. (1967). *Cognitive psychology.* New York: Appleton-Century-Crofts.

Posner, M. I. (1982). Cumulative development of attentional theory. *American Psychologist, 37,* 168–179.

Rumelhart, D. E. (1970). A multicomponent theory of the perception of briefly exposed visual displays. *Journal of Mathematical Psychology, 7,* 191–218.

Shiffrin, R. M., Dumais, S. T., & Schneider, W. (1981). Characteristics of automatism. In J. Long & A. Baddeley (Eds.), *Attention and performance IX* (pp. 223–238). Hillsdale, NJ: Erlbaum.

Sperling, G. (1960). The information available in brief visual presentations. *Psychological Monographs, 74* (11, Whole No. 498).

Sperling, G. (1963). A model for visual memory tasks. *Human Factors, 5,* 19–31.

Sperling, G. (1967). Successive approximations to a model for short-term memory. *Acta Psychologica, 27,* 285–292.

Sperling, G. (1971). The description and luminous calibration of cathode ray oscilloscope visual displays. *Behavioral Research Methods and Instrumentation, 3,* 148–151.

Townsend, J. T., & Ashby, F. G. (1983). *The stochastic modeling of elementary psychological processes.* Cambridge, England: Cambridge University Press.

van der Heijden, A. H. C. (1981). *Short-term visual information forgetting.* London, England: Routledge & Kegan Paul.

von Wright, J. M. (1968). Selection in visual immediate memory. *Quarterly Journal of Experimental Psychology, 20,* 62–68.

Received May 26, 1987
Revision received November 23, 1987
Accepted December 15, 1987 ■