Perception & Psychophysics
1991, 50 (2), 166-178

Mechanisms of attentional selection: Temporally modulated priority tags

STEVEN YANTIS and ELIZABETH JONES
Johns Hopkins University, Baltimore, Maryland

When a single abrupt onset appears in a multielement display, it captures attention. When multiple onset elements occur, they have conditional priority over no-onset elements such that a limited number of onsets can be serviced with high priority in visual search (Yantis & Johnson, 1990). We report three experiments in which we assess two possible mechanisms for attentional prioritization: a priority queue into which a fixed number of high-priority elements are placed for early servicing during search, and a mechanism that temporarily tags all high-priority elements for early servicing or more frequent sampling. We manipulated the visual quality or interletter confusability of the stimuli to prolong encoding and/or comparison operations; this manipulation led to a decrease in the estimated number of elements serviced with high priority. We conclude that a mechanism incorporating temporally decaying priority tags is implicated in servicing multiple abrupt onsets in visual search.

#4

The complexity of visual perception requires an efficient selection mechanism that constrains the current visual task so that it is momentarily tractable (Tsotsos, 1988). Selective attention sets priorities that are used for a variety of visual tasks, including efficient visual search. For example, the guided search model of Cave and Wolfe (1990) suggests that an activation value is computed for each element in a visual display according to its similarity to the target on several dimensions and its conspicuity in the display (i.e., its dissimilarity to nontarget elements). Elements are then processed serially in order of their activation strengths. Similar models have been advanced by others (e.g., Bundesen, 1990; Duncan & Humphreys, 1989; Koch & Ullman, 1985).

These models all include some kind of prioritizing system in which preliminary decisions are made about which stimuli will be processed first (in serial models) or sampled more frequently (in parallel models). In most cases, a distinction is made between bottom-up or stimulus-driven selection, and top-down or goal-directed selection. In the present article, we describe three experiments in which we investigated one aspect of attentional prioritization via stimulus-driven attentional interrupts generated by abrupt visual onsets.

This research was supported by National Institute of Mental Health Grant R01-MH43924 to Steven Yantis. We are grateful to Vibha Thakral and Elizabeth Graham for excellent technical assistance, and to Howard Egeth, Doug Johnson, Jim Johnston, and Toby Mordkoff for valuable suggestions concerning the research. Our thanks to Lester Krueger, John Palmer, and two anonymous reviewers for their helpful comments on an earlier draft of the article. Correspondence should be sent to Steven Yantis, Department of Psychology, Johns Hopkins University, Baltimore, MD 21218 (e-mail: yantis@jhuvms).

Abrupt Onsets and Attention

Several lines of research have provided empirical evidence for attentional capture by abrupt onsets.[1] For example, Todd and Van Gelder (1979) developed the *no-onset* procedure to investigate the effects of abrupt visual onsets in visual detection and discrimination tasks. A no-onset stimulus is presented by first displaying the stimulus camouflaged by irrelevant line segments; when the irrelevant line segments are removed, the no-onset stimulus is revealed. Detection of no-onset stimuli can then be compared to detection of onset stimuli that appear abruptly in previously blank locations. The no-onset procedure is preferable to using gradual onset as a contrast to abrupt onset, because it anchors the presentation of the stimulus in time, which is necessary for measuring reaction time (RT).

Using this procedure, Todd and Van Gelder (1979) found that saccadic eye movements in response to onset stimuli were faster than they were to no-onset stimuli. One possible explanation for this advantage is that abrupt onsets capture visual attention. This hypothesis was investigated by Yantis and Jonides (1984), who examined the efficiency with which subjects could detect a target letter in multielement visual search as a function of whether the target was an onset or a no-onset stimulus. Yantis and Jonides reasoned that if an element with an abrupt onset captures attention, then when the target is an onset, RT should not increase with display size, but when the target is a no-onset, RT should increase linearly with display size as is typical in unguided visual search. Their findings were consistent with the attentional capture hypothesis.[2] Other recent investigations of attentional capture by abrupt onsets include those of Lambert, Spencer, and Mohindra (1987), Müller and Rabbitt (1989), Nakayama and Mackeben (1989), Remington, Johnston, and

Yantis (1990), Warner, Juola, and Koshino (1990), and Yantis and Jonides (1990).

Abrupt Visual Onsets and Attentional Priority

Yantis and Johnson (1990) investigated the mechanism subserving attentional capture by abrupt onset using visual search tasks with displays containing multiple onset and no-onset elements. This arrangement provides a way to determine how attentional priorities are set when there are numerous demands on attention. According to Yantis and Johnson's proposed prioritization model, some number of onset elements (denoted by ϕ) are processed before any no-onset elements are. Once ϕ high-priority elements have been processed, the rest of the display is processed in a random order. Predictions for this model were derived by computing the expected number of serial comparisons required to detect a target, given that ϕ onset elements were processed before any no-onset elements were processed. Here, ϕ ranged from 0 to the total number of onsets in the display.

The reader is referred to Yantis and Johnson (1990) for further details of the predictions and empirical results. For present purposes, we will introduce some of the notation used by Yantis and Johnson (1990) in their analysis of search times. The base model assumes that the elements in the display are scanned one at a time in random order without replacement, until the target is found or all elements have been scanned. This model is expressed as follows:

$$\mathrm{RT} = A+kT+\delta N, \tag{1}$$

where RT is a random variable, A is a random variable representing the duration of all mental operations not included in the other terms of the equation, k is the expected number of serial comparisons required to find the target in a given experimental condition, T is a random variable representing the time required to compare a display element to the target in memory, δ is an indicator variable that equals 1 if the target is absent and 0 otherwise, and N is a random variable representing the amount of additional time required to handle a target-absent trial.

The prioritization model makes predictions for the value of k as a function of display size (number of elements to be scanned) and trial type (target onset, target no-onset, or target absent) under a given value of ϕ. To test the model, the data are subjected to multiple linear regression analysis, and the value of ϕ yielding the best quantitative fit to the data is identified. Yantis and Johnson (1990) conducted three experiments to test the model and to estimate the value of ϕ, and all were consistent with an estimate of $\phi \approx 4$.

Yantis and Johnson (1990) suggested two possible mechanisms for implementing attentional prioritization. First, high-priority elements could be placed into a priority queue with a fixed capacity of ϕ elements. According to this account, the elements in the queue are processed first, followed by the remaining elements in the display. Abrupt onset elements have high priority and are therefore placed in the queue and processed first. When there are more high-priority onset elements present than there are slots in the queue, a subset of ϕ of them are randomly selected for placement in the priority queue.

A second possible mechanism suggested by Yantis and Johnson (1990) to account for their results involves temporally decaying priority tags. According to this account, all high-priority elements are tagged as such, and elements with high tag strengths are processed before (or sampled more frequently than) elements with low tag strengths. Unless they are refreshed, however, the strengths of the priority tags decay over time, so that by the time ϕ tagged elements have been processed, the tag strengths of the high-priority elements are no longer greater than the tag strengths of low-priority elements.[3]

Figure 1 illustrates how this might work. Each panel of the figure illustrates the contents of three different levels of representation: a preattentive representation, containing the unprocessed contents of the visual image; a postattentive representation, containing the identified object tokens corresponding to the elements in the visual scene that have been identified at any given moment (placed in quotation marks to denote their abstract form); and a priority map, representing the current priority tag strength of each element in the scene, as determined by both stimulus-driven (bottom-up) and goal-directed (top-down) factors. The asterisks in the postattentive representation stand for unidentified object tokens, a kind of placeholder, that stand in for objects until they are identified. Each panel in the figure shows the three levels of representation at the beginning of the first three processing epochs, respectively (an epoch is the intercompletion time for the elements in the display, or the amount of time elapsing between the identification of two successively identified elements).

The elements with lines around them in the preattentive representation in Epoch 1 are onset elements, and the other elements in the display are no-onset elements; note that the priority tag strengths of these elements (represented by the diameter of the black circles in the priority map) are stronger than those of the no-onset elements. At the start of Epoch 2, one of the onset elements, "A," has been identified, as indicated by its presence in the postattentive representation. The priority tag of this element has been purged so that it will not be selected again later.[4] At the same time, the tag strengths of the remaining two onset elements have decayed somewhat relative to Epoch 1. At the start of Epoch 3, another onset element, "L," has been identified, and its tag has been purged. The tag strength of the one remaining onset element has decayed further, so that it is no longer greater than the tag strengths of the no-onset elements in the display; therefore, there is no remaining advantage for that element with respect to the no-onset elements in the display. This is what limits the number of onset elements with priority according to the priority tag model. In this example, two onset elements have priority over the no-onset elements.

The idea of what we call *priority tagging* is analogous to corresponding mechanisms in Norman's (1968) theory of memory and attention (i.e., the assignment of "per-

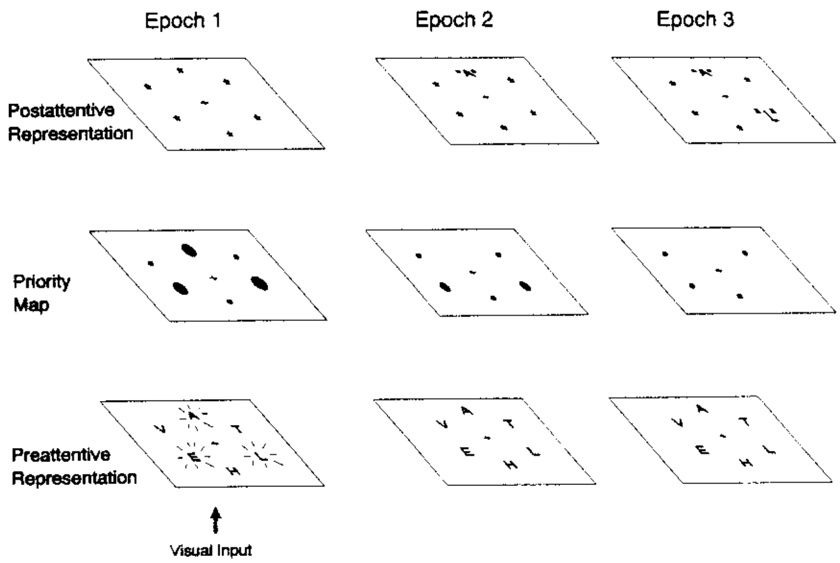

Figure 1. Priority tag strength model. Each epoch represents the amount of time elapsing between successive element identifications. The preattentive representation contains an unprocessed image of the visual field; the postattentive representation contains unidentified object tokens (asterisks) and identified object tokens (e.g., "A"); the priority map contains priority tags whose strengths are proportional to the diameters of the circles in each object location. The elements in the preattentive representation in Epoch 1 with lines around them are onset elements, and have large initial tag strengths; the remaining elements there are no-onsets and have initial tag strengths at baseline. When an element is identified, its tag is set to zero—below baseline—to avoid unnecessary reidentification. Tags that are above baseline spontaneously decay toward baseline if they are not refreshed. See text for further details.

tinence" to certain representations in memory) and in Rumelhart's (1970) visual recognition theory. Analogous ideas have appeared more recently in several other models of attentional selection, including, for example, Koch and Ullman's (1985) saliency values, Duncan and Humphreys's (1989) "attentional weights," Cave and Wolfe's (1990) "attentional activation values," and Bundesen's (1990) "selection weights." Although it has not been suggested that the tag strengths could decay over time, this is not incompatible with previous models, particularly for strengths set by transient signals like abrupt onset.

The experiments reported in this article were designed to distinguish between the two possible mechanisms for attentional priority described above, using the paradigm of Yantis and Johnson (1990). Our approach is to prolong encoding or stimulus comparison operations in the task by manipulating stimulus factors (e.g., visual quality) that are known to slow search. If fixed structural limitations determine the number of onset elements to be processed with priority, then prolonging search time should have no effect on the estimate of ϕ. In contrast, if the time course of priority tag decay determines the number of onset elements to be processed first, then the prolongation of search time, and thus increases in the degree of tag decay for each element that is identified, should reduce the estimate of ϕ.

EXPERIMENT 1

In Experiment 1, we slowed visual search by reducing the contrast of the elements in the display. Visual quality has been shown to slow RT in many different paradigms. Miller and Bauer (1981) found that reducing the contrast of visually presented letters significantly slowed stimulus identification time in a fixed-set memory search task. Similar effects of visual quality on visual search and stimulus identification have been observed elsewhere (e.g., Johnsen & Briggs, 1973; Pashler & Badgio, 1985; Schwartz, Pomerantz, & Egeth, 1977). Loftus (1985) presented evidence that the rate with which information is extracted from visual displays is directly influenced by the contrast of the display (the lower the contrast, the lower the information-extraction rate; see Sperling, 1986, for a quantitative model).

To implement the contrast manipulation, we displayed stimuli on a black background in dark gray for the dim condition and in white for the bright condition. Using a similar manipulation, Pashler and Badgio (1985) obtained an increased RT with dimming of approximately 35–55 msec.[5] In this experiment and in Experiment 2 below, the bright or intact conditions matched the visual conditions employed in the experiments reported by Yantis and Johnson (1990).

The primary prediction of the decaying priority tag model is that the estimate of ϕ should be smaller for dim displays than for bright displays. Furthermore, because the bright condition is very close to an exact replication of Yantis and Johnson's (1990) Experiment 2, the two estimates of ϕ should be similar (approximately 4).

If prolonging search yields no effect on the estimated value of ϕ, however, then a mechanism incorporating a fixed-capacity priority queue is implicated.[6]

Method

Subjects. Fourteen Johns Hopkins University undergraduates (7 males and 7 females) were paid $5.00 per session to participate in two 50-min sessions.

Apparatus and Stimuli. The stimuli were presented on a Princeton SR-12 color monitor controlled by a Sigma Designs Color-400 EGA card in an IBM AT computer. Responses were made by pressing one of two buttons on a panel on the table directly in front of the subject. The stimuli were the letters A, C, E, F, H, J, L, O, P, S, and U. These letters were composed of segments of a seven-segment box-shaped figure eight. Each letter was 0.7° visual angle in height and 0.35° in width, viewed from a distance of approximately 40 cm. There were 12 possible locations spaced at the clock locations (1 o'clock, 2 o'clock, etc.) on an imaginary circle (radius = 6.9°) centered on fixation. Locations on the circle were separated by 3.6° center to center.

In the dim condition, all stimuli appeared in the dark gray available on the computer. In the bright condition, all stimuli appeared in bright white. The background was black, and had a luminance of 1.6 cd/m². The luminance of a square patch composed of bright pixels was 36.8 cd/m², and that of a square composed of dim pixels was 2.2 cd/m². Thus the contrast [defined as $(L_f - L_b)/(L_f + L_b)$, where L_f and L_b are foreground and background luminance, respectively] of the bright pixels was 0.92 and that of the dim pixels was 0.16.

Procedure. On each trial, a target letter appeared in the center of the screen. After 700 msec, this was replaced with a central fixation point along with six figure-eight placeholders distributed in either the even (12 o'clock, 2 o'clock, etc.) or the odd (1 o'clock, 3 o'clock, etc.) locations; whether they occupied the even or the odd locations varied randomly from trial to trial. The locations not occupied by figure-eight placeholders were potential onset locations. The subjects were instructed to maintain fixation on the fixation point throughout each trial (eye position was not monitored). The placeholder display remained on the screen for 1 sec and was then replaced by the search display. In the search displays, half the letters appeared as a result of the removal of segments from the figure-eight placeholders (no-onset elements). The remaining letters (onset elements) were presented in previously blank locations; these appeared at the same time as the camouflaging line segments were removed from the no-onset elements. Placeholders that did not become letters were erased from the screen.

The subjects were to press the right button with the right index finger if the target letter was present in the search display, and the left button with the left index finger if the target letter was absent. If the response was in error or if the subject failed to respond, the computer emitted a 1000-Hz, 200-msec beep. The search display remained on the screen until the subject responded or 2.5 sec had elapsed. The next trial began after a 300-msec intertrial interval.

The subjects were told to respond as quickly as possible while maintaining accuracy. At the end of each block, they received feedback showing their mean RT and number of errors for each of the previous blocks. The relative importance of accuracy over speed was repeatedly stressed. There was a 15-sec enforced break between each block.

Design. Each session of the experiment was divided into eight blocks of 64 trials. Blocks alternated between bright and dim. Whether a session began with a bright or a dim block was counterbalanced across subjects. Display sizes of 4, 6, 8, and 12 elements appeared equally often, and the target was present on half of the trials. On half of the target-present trials the target was an onset element, and on the remaining half it was a no-onset element. Display size and trial type (present/onset, present/no-onset, absent) were factorially combined within each block, and the conditions so formed appeared in random order.

Each session was preceded by a practice block of 20 trials. Each block was preceded by 3 randomly selected warm-up trials. Each error trial was followed by a randomly selected recovery trial. Data from practice, warm-up, and recovery trials were discarded.

Results

Mean correct RTs as a function of display size and trial type (target present/onset, target present/no-onset, target absent) are shown in Figure 2 for the bright and dim conditions. The visual quality manipulation that we used was successful in slowing search, as indicated by the significant visual quality effect (48 ± 11 msec). A three-factor repeated measures analysis of variance (ANOVA) revealed significant main effects of visual quality [$F(1,13) = 17.35$, $p < .01$], trial type [$F(2,26) = 143.83$, $p < .001$], and display size [$F(3,39) = 251.07$, $p < .001$]. Visual quality and display size did not interact significantly [$F(3,39) = 1.15$, $p > .05$], but visual quality and trial type did [$F(2,26) = 5.28$, $p < .05$], as did trial type and display size [$F(6,78) = 68.64$, $p < .001$]. The three-way interaction was also significant [$F(6,78) = 2.58$, $p < .05$].

Because we were primarily interested in the effect of target type (i.e., target present/onset vs. target present/no-onset), a second ANOVA was conducted on the data from target-present trials only. The pattern of results was the same as that above, except that the interaction of visual quality and target type was not reliable. The main effects of visual quality, target type, and display size were all significant [$F(1,13) = 13.02$, $p < .01$; $F(1,13) = 131.77$, $p < .001$; and $F(3,39) = 157.40$, $p < .001$, respectively]. The interaction of target type and display size [$F(3,39) = 35.12$, $p < .001$] and the three-way interaction [$F(3,39) = 5.19$, $p < .01$] were both significant.

The effect of visual quality was larger in target-absent trials than in target-present trials: averaged across display sizes, the effect of visual quality was 63 msec for target-absent trials and 34 msec for target-present trials [$t(13) = 2.43$, $p < .05$]. This is consistent with the results of Pashler and Badgio (1985), who also found that the effect of visual quality was greater in target-absent trials.

The significant three-way interaction of target type, display size, and visual quality indicates that the interaction between target type and display size was different for the bright and dim conditions. As we will see, this reflects a difference in ϕ for the two conditions, which is predicted by the decaying tag model (the value of ϕ specifies the form of the interaction between display size and trial type; cf. Yantis & Johnson, 1990). More detailed analyses of this difference will be described in the Discussion section.

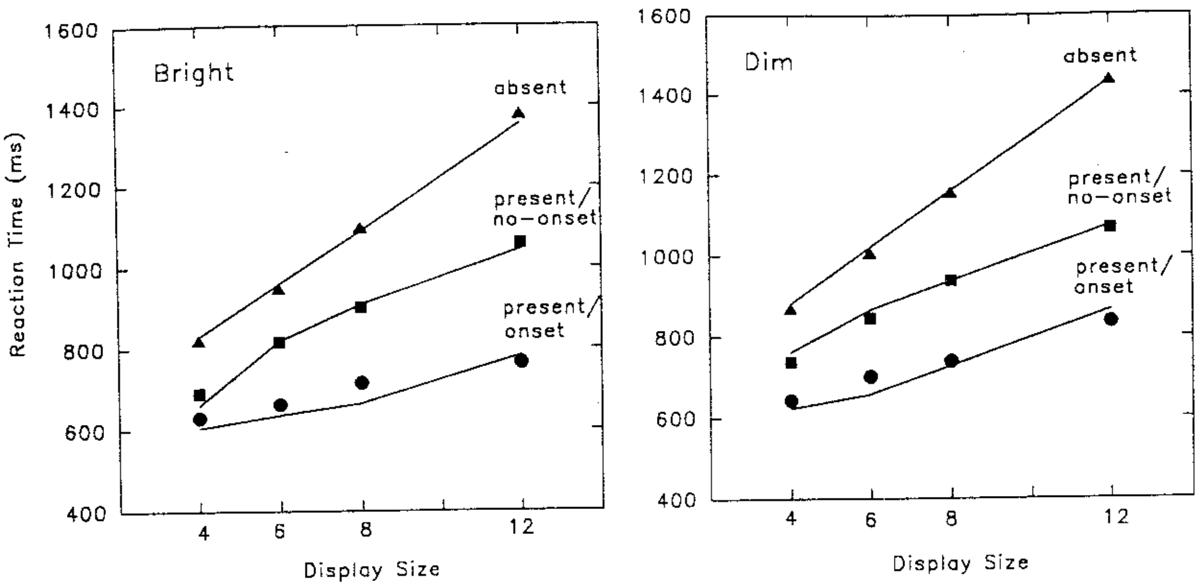

Figure 2. Mean reaction time as a function of trial type and display size in Experiment 1. Left panel: bright condition; right panel: dim condition. In each panel, closed points represent observed data, and solid lines represent best-fitted values according to the prioritization model. For the bright condition, $\phi = 5$, and for the dim condition, $\phi = 3$ (see Table 2).

Separate two-factor ANOVAs were conducted on target-present data for the bright and dim conditions, respectively. For both conditions, the main effects of target type and display size were significant [bright, $F(1,13) = 126.70$ and $F(3,39) = 93.81$, respectively, $p < .001$; dim, $F(1,13) = 111.05$ and $F(3,39) = 133.84$, respectively, $p < .001$]. The interaction of display size and target type was also significant for both bright and dim conditions [$F(3,39) = 30.95$ and $F(3,39) = 16.88$, respectively, $p < .001$].

For both conditions, the main effect of target type indicates that subjects were faster when the target was an onset element than when it was a no-onset element. This rules out the possibility that multiple onset elements cancel each other out so that onset elements have no advantage over no-onset elements (i.e., that $\phi = 0$, as in Model 1 of Yantis & Johnson, 1990). Furthermore, the significant interaction of display size and target type in both conditions rules out a model in which only one onset element is processed before any no-onset elements (i.e., a model with $\phi = 1$). A comparison of the results from both conditions with the predictions of values of $\phi > 1$ will be presented in the Discussion.

Error rates are presented in Table 1. The overall error rate was 4.3%. A three-way repeated measures ANOVA revealed that the error rates mirrored the RT effects described above: there were significant main effects of trial type [$F(2,26) = 119.72$, $p < .001$] and display size [$F(3,39) = 5.57$, $p < .01$]; the main effect of visual quality, however, was not significant ($F < 1$). Visual quality and display size did not interact significantly [$F(3,39) = 1.17$, $p > .05$], but visual quality and trial type did [$F(2,26) = 7.27$, $p < .05$], as did trial type and display size [$F(6,78) = 6.76$, $p < .001$]. The three-way interaction was also significant [$F(6,78) = 2.94$, $p < .05$].

Discussion

The number of comparisons k in each condition given by various values of ϕ were entered as predictor variables into a multiple regression analysis of the mean RTs obtained in Experiment 1. The results of this analysis are summarized in Table 2. For each value of ϕ, two goodness-of-fit measures (proportion of variance accounted for, R^2, and root mean square error, *RMSE*) are listed.

For the bright condition, the best-fitting value of ϕ was 5; this accounted for 98.5% of the variance. Values of 3, 4, and 6 also accounted for a substantial amount of the variance (98.1%, 98.4%, and 98.1%, respectively). For the dim condition, the best-fitting value of ϕ was 3, accounting for 99.0% of the variance. Values of 2, 4, and 5 also accounted for a substantial amount of the variance (98.4%, 98.6%, and 98.0%, respectively). This reduc-

Table 1
Error Rates (in Percent) in Each Condition of Experiment 1

	Display Size			
Trial Type	4	6	8	12
	Bright			
Present/Onset	3.6	3.1	3.1	4.7
Present/No-onset	3.6	6.0	10.9	12.7
Absent	2.0	1.5	1.7	4.5
	Dim			
Present/Onset	2.5	3.3	2.9	4.0
Present/No-onset	3.6	7.4	10.7	13.6
Absent	1.7	2.1	2.3	5.2

tion in the estimated value of ϕ as search is prolonged is consistent with the prediction of the decaying priority tag model.

For illustrative purposes, the observed mean RTs (closed points) are shown in Figure 2 plotted with the predicted RTs (solid lines) for the best-fitting values of ϕ ($\phi = 5$ for the bright condition and $\phi = 3$ for the dim condition).

A more specific prediction concerning the size of the difference in our estimates of ϕ for the two conditions is made by the decaying tag model. The model predicts a difference in the estimate of ϕ for the bright and dim conditions ($\Delta\phi$) of Q/T, where Q is the size of the visual quality effect and T is the mean time to process one item in the display (Equation 1). This prediction arises as follows. In the bright condition, ϕ elements are processed with priority before the tags decay to baseline. In the dim condition, search is slowed overall by Q msec relative to the bright condition, allowing the priority tags to decay further during search. For every T msec that search is prolonged by reducing visual quality, one fewer onset element can be processed with high priority. For example, if $Q = T$, then the quality manipulation is equivalent to prolonging search, and therefore to letting the tags decay, for the amount of time required to process one element, which would result in a reduction in ϕ of 1. More generally, the predicted change in ϕ equals the ratio of Q to T; thus, $\Delta\phi = Q/T$.

Dimming the stimuli in Experiment 1 slowed visual search by 34 msec on target-present trials. The multiple regression analysis yielded estimates of T, the mean time required to scan one element (Equation 1), of 62.0 and 69.8 msec for the bright and dim conditions, respectively. The tag model therefore predicts $\Delta\phi = Q/T \approx 0.5$. The observed value of $\Delta\phi$ for the group is 2, which does not match the prediction closely. However, the procedure for estimating ϕ used here constrains the estimate to be an integer value; because the best estimates of ϕ range from 2 to 5 for dim and 3 to 6 for bright, the predicted difference of 0.5 is broadly consistent with our results.

Furthermore, the foregoing method for estimating ϕ is not precise. This is reflected in the fact that for both contrast conditions, several values of ϕ accounted for a substantial and similar proportion of the variance (see Table 2), in part because the predicted patterns of k under different values of ϕ are highly correlated. In order to obtain a converging estimate of ϕ, and to determine whether individual subjects exhibited a pattern of results similar to that of the group, we conducted separate regression analyses for each subject, using each subject's mean RT from each condition of the experiment.

The quantitative fit of the data from each subject to the model was good: for all subjects, the best-fitting value of ϕ accounted for more than 93% of the variance. Best-fitting values of ϕ for each subject under each quality condition are shown in Figure 3. The mean values of ϕ were 4.17 and 3.42 for the bright and dim conditions, respectively; the difference $\Delta\phi$ was 0.75 ± 0.37. For both conditions, the estimates ranged from 1 to 6 across subjects. The best-fitting value of ϕ was greater in the bright than in the dim condition for 7 subjects, it was the same for 6 subjects, and it was smaller in the bright than in the dim condition for 1 subject. This result is consistent with the predictions of a decaying tag model, although the difference is not significant by a sign test ($p = .055$).

A further prediction of the decaying tag model is that the value of $\Delta\phi$ for each subject in Figure 3 should be related to the magnitude of the stimulus-quality effect for that subject (i.e., $\Delta\phi_s = Q_s/T_s$ for each subject s). This follows from the assumption that the decrease in ϕ arises because more time elapses during search in the dim condition, allowing the tags to decay further. In fact, across subjects, the magnitude of visual quality effect was uncorrelated with the magnitude of $\Delta\phi$ ($r = .08$, n.s.). On the surface, this appears to undermine the decaying tag model. Closer analysis reveals, however, that this lack of correlation may be due to the restricted range of both variables. For most subjects, $\Delta\phi$ was 0 or 1 (only 3 subjects had differences larger than this). Furthermore, for most subjects the visual quality effect ranged from 25 to 63 msec (only 2 subjects had effects outside this range). Such restrictions in range can significantly diminish the size of the correlation coefficient (see, e.g., Edwards, 1976, pp. 60-61).

Table 2
Multiple Regression Analysis of Experiment 1

ϕ	R^2	*RMSE*
	Bright Condition	
0	.854	92
1	.928	65
2	.965	45
3	.981	33
4	.984	30
5*	.986	29
6	.981	33
	Dim Condition	
0	.888	86
1	.954	55
2	.984	33
3*	.990	26
4	.986	30
5	.980	37
6	.968	46

Note—R^2 is the proportion of variance accounted for in the regression analysis. *RMSE* is root mean square error, defined as $[(1/n)\sum_i(\mathrm{obs}_i - \mathrm{pred}_i)^2]^{1/2}$, where n is the number of points in the model, and obs_i and pred_i are the observed and predicted values for point i, respectively. *Best fit.

EXPERIMENT 2

In order to further test the decaying tag mechanism, which was tentatively supported in Experiment 1, we used a second degradation manipulation in Experiment 2 to prolong search time. If the decaying tag account is correct, then $\Delta\phi$ should not depend on the method used to prolong search; instead, it should depend on Q, the size

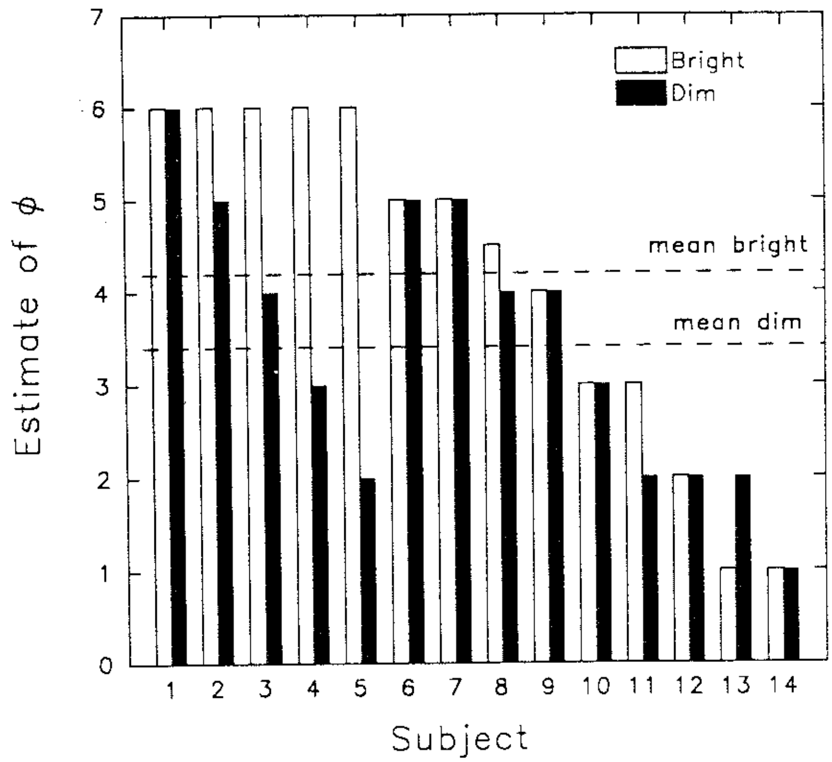

Figure 3. Best-fitting value of ϕ for each subject in Experiment 1. Open bars: bright condition; filled bars: dim condition. Horizontal dashed lines represent mean value of ϕ across subjects for the bright and dim conditions, respectively.

of the degradation effect. In Experiment 2, we prolonged search by adding visual noise (randomly placed dots) over each letter position.

Although the error rate in Experiment 1 was only 4.3% overall, error rates in some conditions with large display sizes were as high as 13.6%, an undesirably high level. Most of these errors occurred on target-present trials, and we speculated that they stemmed from a *deadline* strategy employed by subjects in which they would respond "no" if they had not detected the target by the time a subjective deadline had been reached (this is a choice RT variant of the deadline model described by Ollman & Billington, 1972). These deadline responses would tend to occur in the target-present trials involving relatively large display sizes and no-onset targets. In order to discourage the deadline strategy and thereby reduce the error rate, we changed our response requirements from a yes/no choice task to a go/no-go task (a variant of a Donders Type C reaction). Because a response was not required when the target was absent, the subjects could be expected to continue searching for the target until the response interval expired, providing a better estimate of the true RT in the most difficult conditions.

Method

Subjects. Twelve Johns Hopkins University undergraduates were each paid $4.50 for participation in a single session in Experiment 2; none had participated in Experiment 1.

Apparatus and Stimuli. These were the same as in Experiment 1, except that the stimuli were always bright, and, in the degraded condition, a cluster of seven dots was randomly superimposed on each letter location. Each dot consisted of a single pixel (approximately 0.02° in height). The seven dots were positioned so that each one had an equal probability of falling on any of the pixels (including those constituting the letter contours themselves) in a rectangular region centered on each letter that was 0.8° in height and 0.4° in width (recall that the letters were 0.7° in height and 0.35° in width). The lines making up the letters were one pixel wide. The dots were placed in different random locations for each letter position and were repositioned randomly on each trial.

Procedure. The procedure was identical to that of Experiment 1, with the following exceptions. First, subjects were to press a single key with the dominant hand when the target was present, and they were to withhold a response if the target was absent (go/no-go responding).

Second, in the degraded condition, a cluster of seven randomly placed dots was superimposed on each of the possible element locations at the start of the trial, and remained there throughout the trial. The dots appeared at the same time as the figure eights appeared, yielding 6 locations with dots alone and 6 locations containing both dots and figure eights. After 1 sec, the search display appeared; depending on display size, two, three, four, or six letters appeared in non-figure-eight locations (onset letters), and line segments were removed to reveal letters in two, three, four, or six of the figure eights (no-onset letters). The figure eights that did not change to letters on that trial (four, three, two, or zero of them for Display Sizes 4, 6, 8, and 12, respectively) disappeared. In all cases, the noise dots remained static in all 12 locations from figure-eight onset until the subject responded, regardless of whether that location contained an onset, a no-onset, a disappearing figure eight,

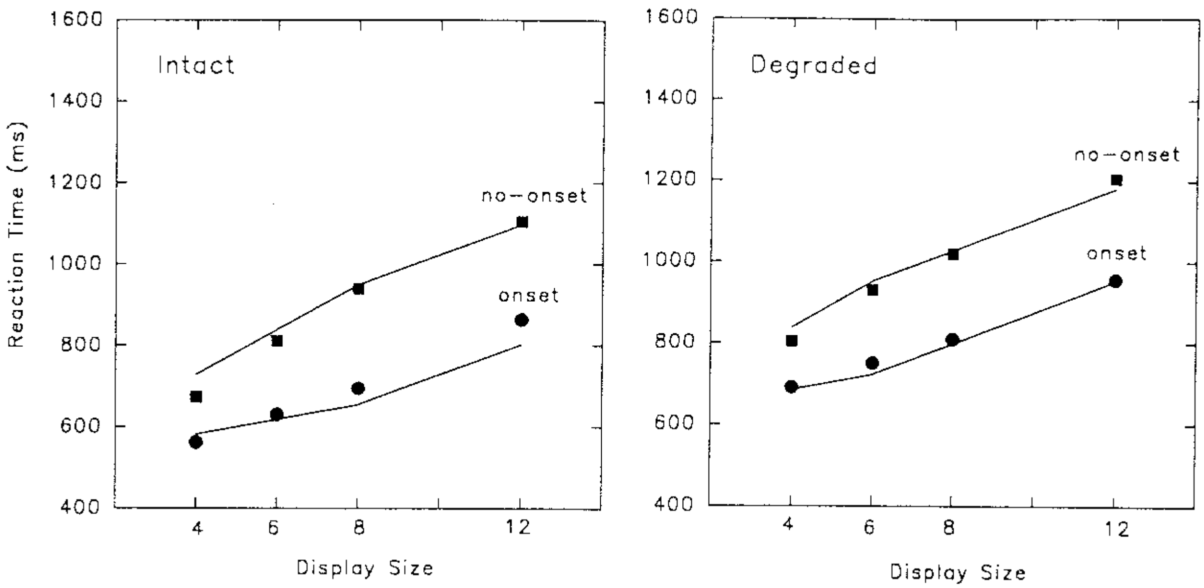

Figure 4. Mean reaction time as a function of trial type and display size in Experiment 2. Left panel: intact condition; right panel: degraded condition. In each panel, closed points represent observed data, and solid lines represent best-fitting values according to the prioritization model. For the intact condition, $\phi = 4$, and for the degraded condition, $\phi = 3$ (see Table 4).

or no stimulus. In the intact condition, the procedure was identical to that for the bright condition of Experiment 1, except that responding consisted of go/no-go.

Design. There were 10 blocks of 48 trials each, and a target was present on two thirds of the trials in each block. When a target was present, it was equally often an onset and a no-onset element. Otherwise, the design details were the same as they had been in Experiment 1, except that the bright and dim conditions were replaced by intact and degraded conditions, respectively, which alternated between blocks.

Results

Mean correct RTs as a function of display size and trial type (target present/onset and target present/no-onset) are shown for the intact and degraded conditions in Figure 4. As in Experiment 1, the visual quality manipulation was successful: adding noise dots slowed search (mean overall effect of 109 ± 8 msec). An ANOVA revealed significant main effects of visual quality [$F(1,11) = 205.17$, $p < .001$], trial type [$F(1,11) = 27.55$, $p < .001$], and display size [$F(3,33) = 231.13$, $p < .001$]. The only significant interaction was that between trial type and display size [$F(3,33) = 11.11$, $p < .001$] (all other Fs < 1).

Two-factor ANOVAs were then conducted separately for the intact and degraded conditions. In both cases, the main effects of trial type and display size were significant [intact, $F(1,11) = 26.56$ and $F(3,33) = 135.80$, respectively, $p < .001$; degraded, $F(1,11) = 17.36$, $p < .01$, and $F(3,33) = 188.61$, $p < .001$, respectively]. The interaction of display size and target type was also significant for both intact and degraded conditions [$F(3,33) = 7.60$, $p < .001$, and $F(3,33) = 5.43$, $p < .01$, respectively].

Error rates are presented in Table 3. The overall error rate was 2.5%. Error rates in target-present conditions were much lower than they were in Experiment 1; evidently the switch to a go/no-go task successfully discouraged the use of a "time-out" strategy. A three-factor ANOVA on the error rates revealed significant main effects of visual quality [$F(1,11) = 7.40$, $p < .05$], trial type [$F(2,22) = 5.65$, $p < .05$], and display size [$F(3,33) = 3.45$, $p < .05$]. None of the interaction terms were significant (all Fs < 1).

Discussion

Mean RT across subjects for each condition was entered into the regression analysis (summarized in Table 4). Because responses were not collected on target-absent trials, Equation 1 was modified for purposes of this analysis to exclude the final term, which reflects the additional amount of time to deal with negative trials (or, to put it another way, δ was always set to 0). For the intact condition, the best-fitting value of ϕ was 4; this accounted for

Table 3
Error Rates (in Percent) in Each Condition of Experiment 2

	Display Size			
Trial Type	4	6	8	12
	Intact Condition			
Present/Onset	0.0	0.4	1.2	2.1
Present/No-onset	1.7	1.2	0.8	2.1
Absent	3.3	2.5	4.6	2.5
	Degraded Condition			
Present/Onset	1.2	0.8	2.9	2.9
Present/No-onset	2.1	2.1	1.7	4.1
Absent	2.1	5.4	5.4	5.8

Note—Errors on target-present trials are misses; errors on target-absent trials are false alarms.

Table 4
Multiple Regression Analysis of Experiment 2

ϕ	R^2	*RMSE*
	Intact Condition	
0	.640	117
1	.888	65
2	.956	41
3	.971	33
4*	.976	30
5	.931	51
6	.895	63
	Degraded Condition	
0	.611	113
1	.871	65
2	.970	31
3*	.984	23
4	.967	33
5	.949	41
6	.920	51

Note—R^2 is the proportion of variance accounted for in the regression analysis. *RMSE* is root mean square error, defined as $[(1/n)\sum_i(\text{obs}_i - \text{pred}_i)^2]^{1/2}$, where n is the number of points in the model, and obs_i and pred_i are the observed and predicted values for point i, respectively. *Best fit.

97.6% of the variance. For the degraded condition, the best-fitting value of ϕ was 3, accounting for 98.4% of the variance. The reduction in ϕ from 4 to 3 is consistent with the decaying tag model. The predicted RTs for the best-fitting values of ϕ are plotted in Figure 4 (solid lines).

The tag model also predicts that $\Delta\phi = Q/T$ (see the Discussion section of Experiment 1 for details). In Experiment 2, $Q = 109$ and $T = 71.3$ and 78.2 for the intact and degraded conditions, respectively. These values yield a predicted value of $\Delta\phi \approx 1.45$; this is broadly consistent with the obtained value of 1.

Next, we conducted separate regression analyses for each subject; the results of this analysis are summarized in Figure 5. As in Experiment 1, the quantitative fit of the data from each subject was good: the best-fitting value of ϕ accounted for more than 89% of the variance for all subjects. The mean values of ϕ were 3.83 and 3.08 for the intact and degraded conditions, respectively; the difference $\Delta\phi$ was 0.75 ± 0.35. The best-fitting value of ϕ was greater in the intact than in the degraded condition for 8 subjects, it was the same for 3 subjects, and it was

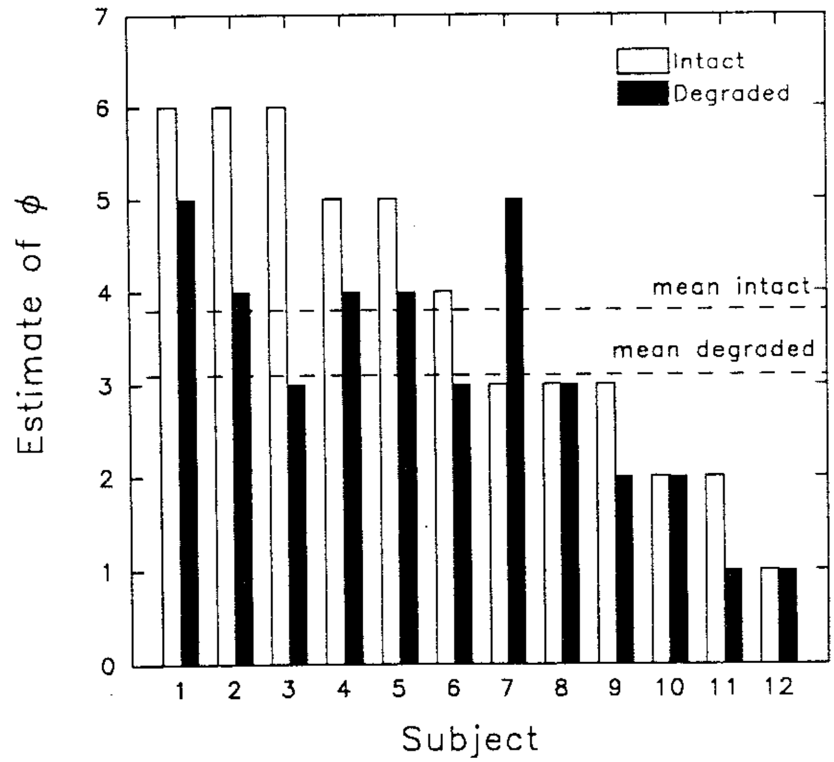

Figure 5. Best-fitting value of ϕ for each subject in Experiment 2. Open bars: intact condition; filled bars: degraded condition. Horizontal dashed lines represent mean value of ϕ across subjects for the intact and degraded conditions, respectively.

smaller in the intact than in the degraded condition for 1 subject. This result is consistent with the predictions of a decaying tag model, and the difference is significant by a sign test ($p < .05$).

EXPERIMENT 3

In both Experiments 1 and 2, we caused slowing in visual search by reducing stimulus quality. One possible consequence of visual degradation is that the salience of the attentional interrupt signal generated by the onset stimuli is attenuated relative to undegraded conditions. This might lead to a reduction in the estimated number of elements serviced with priority. In order to ensure that our results were not due to the stimulus quality manipulation per se, but that they instead implicated the underlying prioritization mechanism, it was necessary to carry out an additional experiment in which search was slowed in a different way.

It is well known that stimulus identification and visual search are slower when stimuli are relatively complex and/or confusable than when the stimuli are simple and highly distinct (see, e.g., Duncan & Humphreys, 1989). Preliminary experiments with the no-onset letters used in these experiments revealed that visual search with the subset A, E, H, P, and S was considerably slower than with the subset C, J, L, O, and U. We will refer to the subset consisting of A, E, H, P, and S as the complex stimulus set and the subset consisting of C, J, L, O, and U as the simple stimulus set.[7]

The display sizes in Experiment 3 were 4, 8, 12, and 16, as opposed to 4, 6, 8, and 12 in Experiments 1 and 2. We increased the range of display sizes because the best-fitting values of ϕ were 6 or greater for several subjects in Experiments 1 and 2. In those experiments, the largest number of onsets in a display was 6 (when display size was 12), and this permitted us to make estimates of ϕ only up to and including 6, but not more (see Yantis & Johnson, 1990). By extending the range of display sizes to 16 in Experiment 3, we were able to estimate values of ϕ up to 8.

If onsets are accorded high priority via the binding of temporally decaying tags, we should observe a reduction in the value of ϕ when visual search is slowed by changes in the discriminability of the stimulus set (simple vs. complex) that is similar to the change observed in Experiments 1 and 2 when search was slowed by changes in stimulus quality. The structural queue model predicts no difference in the estimate of ϕ.

Method

Subjects. Fourteen Johns Hopkins University undergraduates (12 males and 2 females) participated in two 50-min sessions in partial fulfillment of a course requirement. None had participated in Experiment 1 or 2.

Apparatus and Stimuli. The apparatus was the same as in Experiments 1 and 2. The stimuli were the letters A, E, H, P, and S for the complex stimulus set and C, J, L, O, and U for the simple stimulus set. As before, the letters were presented in a circular formation around a central fixation point. In Experiment 3, there were 16 possible locations on the imaginary circle separated by 2.7° center to center. All letters appeared in yellow on a black background.

Procedure. The procedure was the same as that for the bright condition in Experiment 1, except that responding consisted of go/no-go, as in Experiment 2.

Design. The design was the same as in Experiment 2, with the following exceptions. The experiment was divided into eight blocks of 48 trials. In each block there were equal numbers of trials with the complex and simple stimulus sets, and these varied randomly from trial to trial. The target was present on two thirds of the trials. On half of the target-present trials, the target was an onset element,

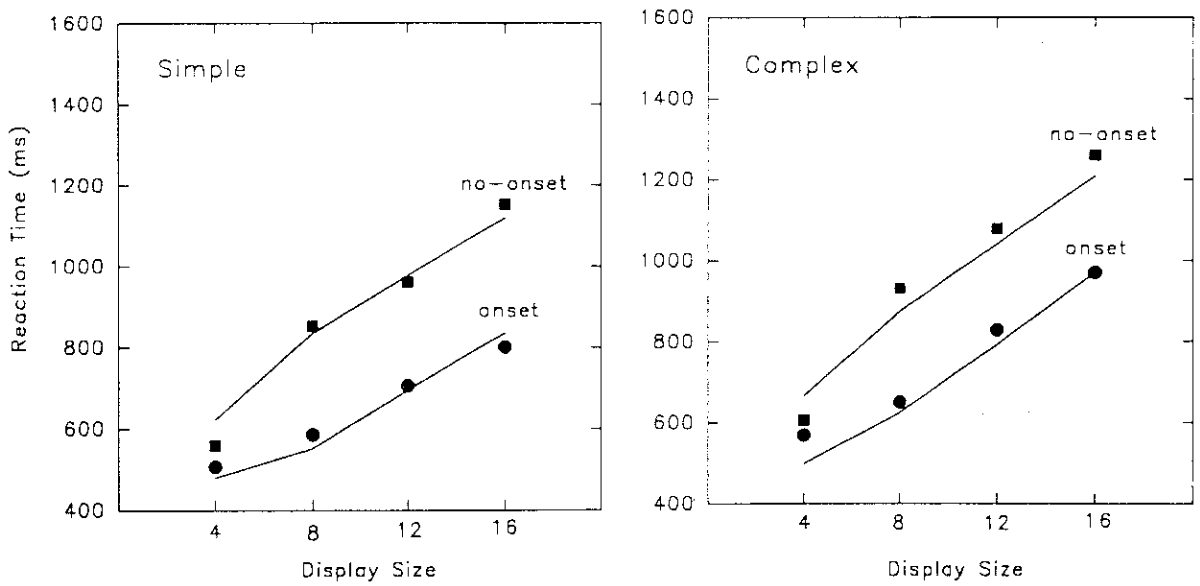

Figure 6. Mean reaction time as a function of target type and display size in Experiment 3. Left panel: simple stimulus set; right panel: complex stimulus set. In each panel, closed points represent observed data, and solid lines represent best-fitting values according to the prioritization model. For the simple stimulus set, $\phi = 4$, and for the complex stimulus set, $\phi = 3$ (see Table 6).

and on half it was a no-onset element. The remaining design details were as in Experiments 1 and 2.

Results

Mean correct RTs are shown in Figure 6 as a function of display size and target type (target present/onset, target present/no-onset) for the simple and complex stimulus conditions, respectively. The effect of stimulus complexity was 96 ± 16 msec in Experiment 3. A three-factor repeated measures ANOVA revealed significant main effects of stimulus complexity [$F(1,13) = 32.80, p < .001$], target type [$F(1,13) = 97.21, p < .001$], and display size [$F(3,39) = 484.03, p < .001$]. Stimulus complexity and display size interacted significantly [$F(3,39) = 4.83$, $p < .01$], as did target type and display size [$F(3,39) = 45.52, p < .001$]. Neither the stimulus complexity $\times$ target type interaction [$F(1,13) = 1.80, p > .05$] nor the three-way interaction [$F(3,39) = 0.78$] was significant.

Separate two-factor ANOVAs were conducted on data from the simple and complex stimulus conditions. For both conditions, the main effects of target type and display size were significant [simple: $F(1,13) = 109.70, p < .001$, and $F(3,39) = 198.11, p < .001$, respectively; complex: $F(1,13) = 74.73, p < .001$, and $F(3,39) = 312.56$, $p < .001$, respectively]. The interaction of display size and target type was also significant for both simple and complex conditions [$F(3,39) = 21.08, p < .001$, and $F(3,39) = 27.32, p < .001$, respectively].

Error rates are presented in Table 5. The overall error rate was 1.7%. A three-factor ANOVA revealed a significant main effect of display size [$F(3,39) = 10.33$, $p < .001$]. No other main effects or interactions reached significance.

Discussion

Regression analyses were conducted to identify the best-fitting value of ϕ; the results are summarized in Table 6. The predicted RTs for the estimated values of ϕ are shown in Figure 6 (solid lines). For the simple stimulus condition, $\phi = 4$ yielded the best fit; it accounted for 97.4% of the variance. For the complex stimulus condition, $\phi = 3$ yielded the best fit, accounting for 97.5% of the variance. As in Experiments 1 and 2, these results are consistent with the prediction of the decaying tag model: the estimate of ϕ was smaller with the complex stimulus set (slow search) than it was with the simple stimulus set (rapid search).

In Experiment 3, $Q = 96$ and $T = 71.1$ for the simple stimulus condition and 83.4 for the complex stimulus condition (this difference reflects the significant interaction between stimulus complexity and display size). The change in ϕ predicted by the tag model is $\Delta\phi = Q/T \approx 1.25$. As before, the observed change of 1 is consistent with this prediction.

As in Experiments 1 and 2, several different values of ϕ accounted for a similar and significant proportion of the variance (Table 6). We therefore conducted regression analyses on individual subject data again; the best-fitting values of ϕ for each subject in each condition are shown in Figure 7. For all but 1 of the 14 subjects, the best-fitting value of ϕ accounted for more than 87% of the variance. The mean values of ϕ were 5.07 and 3.14 for the simple and complex stimulus conditions, respectively; the difference $\Delta\phi$ was 1.93 ± 0.53. Across subjects, ϕ varied from 1 to 6 in the complex stimulus condition and from 1 to 8 in the simple stimulus condition. The best-fitting value of ϕ was greater in the simple than in the complex stimulus condition for 10 subjects, it was the same for 3 subjects, and it was smaller in the simple than in the complex stimulus condition for 1 subject. This dif-

Table 5
Error Rates (in Percent) in Each Condition of Experiment 3

Trial Type	Display Size 4	8	12	16
	Simple Stimulus Set			
Present/Onset	1.8	1.5	3.0	3.0
Present/No-onset	0.3	0.0	0.3	1.8
Absent	0.3	1.3	0.8	2.7
	Complex Stimulus Set			
Present/Onset	1.0	3.0	3.0	2.7
Present/No-onset	0.8	0.8	1.5	3.9
Absent	0.5	0.3	0.8	4.9

Note—Errors on target-present trials are misses; errors on target-absent trials are false alarms.

Table 6
Multiple Regression Analysis of Experiment 3

ϕ	R^2	*RMSE*
	Simple Stimulus Set	
0	.609	149
1	.781	112
2	.886	81
3	.952	52
4*	.974	38
5	.968	43
6	.954	51
7	.947	55
8	.933	62
	Complex Stimulus Set	
0	.729	134
1	.875	91
2	.942	62
3*	.975	41
4	.967	47
5	.944	61
6	.904	79
7	.884	87
8	.859	96

Note—R^2 is the proportion of variance accounted for in the regression analysis. *RMSE* is root mean square error, defined as $[(1/n)\sum_i(\text{obs}_i - \text{pred}_i)^2]^{1/2}$, where n is the number of points in the model, and obs_i and pred_i are the observed and predicted values for point i, respectively. *Best fit.

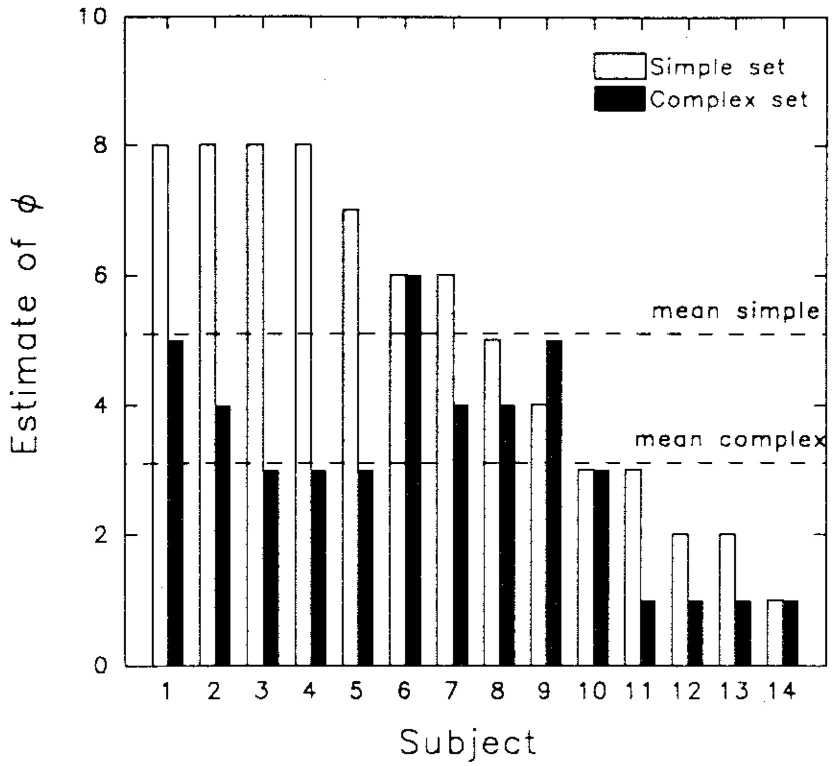

Figure 7. Best-fitting value of ϕ for each subject in Experiment 3. Open bars: simple stimulus set; filled bars: complex stimulus set. Horizontal dashed lines represent mean value of ϕ across subjects for the simple and complex stimulus sets, respectively.

ference is significant by a sign test ($p < .01$). Again, this is consistent with the predictions of the tag model.

GENERAL DISCUSSION

To summarize, we conducted three experiments that yielded results consistent with the predictions of a temporally decaying priority tag model. In Experiment 1, the estimate of ϕ was larger for bright than for dim displays; this held for both group means and individual subjects. A similar result was obtained in Experiment 2, when the slowing of visual search was caused by superimposing visual noise on the stimulus letters. In Experiment 3, the estimates of ϕ were larger for the simple stimulus set (rapid search) than for the complex stimulus set (slower search).

Together, these results provide a converging body of support for the priority tag model. The specific quantitative predictions of the decaying tag model were satisfied only approximately, and the regression fits carried out on the group data from the three experiments provided only qualitative support for the predicted change in ϕ. In each case, the fits to other nearby values of ϕ were almost as good as those illustrated in Figures 2, 4, and 6. Nevertheless, when search was prolonged (using three different methods), the estimated value of ϕ decreased in 24 of the 40 subjects studied here, remained unchanged in 13 subjects, and increased in only 3 subjects. Clearly, the value of ϕ is not fixed, and this fact seriously undermines an account of attentional prioritization that incorporates a queue with a fixed number of slots.

It is possible that the decaying strength of the priority tags over time observed in these experiments applies only to transient high-priority events such as abrupt onset or movement, and not to persisting selection cues such as color, location, or shape. For example, Egeth, Virzi, and Garbart (1984) showed that when searching a display of red and black elements, subjects could successfully limit their search to the red elements only, when they were designated as high priority in the instructions (i.e., the target could only be red). This suggests that it is possible to process all high-priority elements before any low-priority elements when priority is determined by stimulus attributes, such as color, that are continuously available throughout the duration of search. In terms of the present account, the priority tags associated with such cues do not decay, but are continuously or periodically refreshed.

The results of the present experiments provide evidence for a mechanism employing attentional tags that decay with time if they are not refreshed (Figure 1). Further experiments involving other attentional cues can be carried out to assess whether this mechanism generalizes to these other domains.

REFERENCES

BUNDESEN, C. (1990). A theory of visual attention. *Psychological Review*, **97**, 523-547.

CAVE, K. R., & WOLFE, J. M. (1990). Modelling the role of parallel processing in visual search. *Cognitive Psychology*, **22**, 225-271.

DUNCAN, J., & HUMPHREYS, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, **96**, 433-458.

EDWARDS, A. L. (1976). *An introduction to linear regression and correlation*. San Francisco: W. H. Freeman.

EGETH, H. E., VIRZI, R. A., & GARBART, H. (1984). Searching for conjunctively defined targets. *Journal of Experimental Psychology: Human Perception & Performance*, **10**, 32-39.

JOHNSEN, A. M., & BRIGGS, G. E. (1973). On the locus of display load effects in choice reactions. *Journal of Experimental Psychology*, **99**, 266-271.

JONIDES, J., & IRWIN, D. E. (1981). Capturing attention. *Cognition*, **10**, 145-150.

KLEIN, R. (1988). Inhibitory tagging system facilitates visual search. *Nature*, **334**, 430-431.

KOCH, C., & ULLMAN, S. (1985). Shifts in selective visual attention: Toward the underlying neural circuitry. *Human Neurobiology*, **4**, 219-227.

LAMBERT, A., SPENCER, E, & MOHINDRA, N. (1987). Automaticity and the capture of attention by a peripheral display change. *Current Psychological Research & Reviews*, **6**, 136-147.

LOFTUS, G. R. (1985). Picture perception: Effects of luminance on available information and information-extraction rate. *Journal of Experimental Psychology: General*, **114**, 342-356.

MILLER, J., & BAUER, D. (1981). Visual similarity and discrimination demands. *Journal of Experimental Psychology: General*, **110**, 39-55.

MÜLLER, H. J., & RABBITT, P. M. A. (1989). Reflexive and voluntary orienting of visual attention: Time course of activation and resistance to interruption. *Journal of Experimental Psychology: Human Perception & Performance*, **15**, 315-330.

NAKAYAMA, K., & MACKEBEN, M. (1989). Sustained and transient components of focal visual attention. *Vision Research*, **29**, 1631-1647.

NORMAN, D. A. (1968). Toward a theory of memory and attention. *Psychological Review*, **75**, 522-536.

OLLMAN, R. T., & BILLINGTON, M. J. (1972). The deadline model for simple reaction times. *Cognitive Psychology*, **3**, 311-336.

PASHLER, H., & BADGIO, P. (1985). Visual attention and stimulus identification. *Journal of Experimental Psychology: Human Perception & Performance*, **11**, 105-121.

REMINGTON, R., JOHNSTON, J. C., & YANTIS, S. (1990). *Involuntary attentional capture by abrupt onset*. Manuscript submitted for publication.

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

SCHWARTZ, S. P., POMERANTZ, J. R., & EGETH, H. E. (1977). State and process limitations in information processing: An additive factors analysis. *Journal of Experimental Psychology: Human Perception & Performance*, **3**, 402-410.

SPERLING, G. (1986). A signal-to-noise theory of the effects of luminance on picture memory: Comment on Loftus. *Journal of Experimental Psychology: General*, **115**, 189-192.

TODD, J. T., & VAN GELDER, P. (1979). Implications of a transient-sustained dichotomy for the measurement of human performance. *Journal of Experimental Psychology: Human Perception & Performance*, **5**, 625-636.

TOWNSEND, J. T., & ASHBY, F. G. (1983). *Stochastic modeling of elementary psychological processes*. Cambridge, U.K.: Cambridge University Press.

TSOTSOS, J. K. (1988). A "complexity level" analysis of immediate vision. *International Journal of Computer Vision*, **1**, 303-320.

WARNER, C. B., JUOLA, J. F., & KOSHINO, H. (1990). Voluntary allocation versus automatic capture of visual attention. *Perception & Psychophysics*, **48**, 243-251.

WOLFE, J. M., & POKORNY, C. W. (1990). Inhibitory tagging in visual search: A failure to replicate. *Perception & Psychophysics*, **48**, 357-362.

YANTIS, S., & JOHNSON, D. N. (1990). Mechanisms of attentional priority. *Journal of Experimental Psychology: Human Perception & Performance*, **16**, 812-825.

YANTIS, S., & JONIDES, J. (1984). Abrupt visual onsets and selective attention: Evidence from visual search. *Journal of Experimental Psychology: Human Perception & Performance*, **10**, 601-621.

YANTIS, S., & JONIDES, J. (1990). Abrupt visual onsets and selective attention: Voluntary versus automatic allocation. *Journal of Experimental Psychology: Human Perception & Performance*, **16**, 121-134.

NOTES

1. By *attentional capture*, we refer to the deployment of attention to an object in a stimulus-driven, rather than goal-directed, fashion. See Jonides and Irwin (1981), Yantis and Jonides (1984, 1990), and Yantis and Johnson (1990) for further discussion.

2. An alternative account of these results was that no-onset stimuli were simply more difficult to perceive, because of (e.g.) forward masking. This account has been ruled out by experiments in which attention was directed in advance to the location of an upcoming onset or no-onset letter; in these experiments, no RT difference was observed (Yantis & Jonides, 1984, 1990). Thus, only when attention is diffuse do onset stimuli evidence an advantage over no-onset stimuli.

3. Our experiments cannot definitively distinguish serial from parallel models (Townsend & Ashby, 1983). As pointed out below and by Yantis and Johnson (1990, Appendices A and B), both a serial and a parallel implementation of the present model are available. According to the serial version, the object with the highest priority tag strength is selected and identified first, followed by the element with the next highest strength, and so forth. According to the parallel limited-capacity version, all elements are continuously sampled in parallel, and the frequency of sampling is proportional to the strength of the corresponding priority tag. Elements that are sampled more frequently will be identified more rapidly. Total finishing time will be determined by a race between the sampling processes associated with each element. We make no strong claims about whether the serial or the parallel version of the model is correct.

4. Note that this provides a possible mechanism for inhibition of return (cf. Klein, 1988, and Wolfe & Pokorny, 1990, for a discussion).

5. Note that the quality manipulation need not slow down search *rate* (i.e., the slope of the display-size function); it only has to increase the amount of time that elapses between display onset and when the target is found. Indeed, Pashler and Badgio (1985) found no interaction between display size and visual quality; thus no such interaction is predicted here either.

6. One possible undesirable consequence of slowing search with visual degradation might be to impair the effectiveness with which abrupt onsets capture attention. This possibility is addressed in Experiment 3, where search is slowed by increasing the interstimulus confusability of the display elements.

7. The terms *complex* and *simple* are merely heuristic; they are derived from the relative number of line segments of the letters in the two sets. The difference in visual search speed between the two sets is probably a function of the discriminability of the letters within each set. For our purposes in this experiment, however, it is not necessary to have a full explanation of the observed slowdown in search.

(Manuscript received September 28, 1990;
revision accepted for publication March 6, 1991.)