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The effect of adapting luminance on the latency of visual search [1]

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Abstract

Computational models of attentional processing typically view the ‘‘attentional spotlight’’ as a winner-take-all network whose focus can be shifted serially about a display if required. As a result, lateral inhibition is assumed in these models to be an important mechanism involved in visual search. On the basis of this assumption, we predicted that changes in adapting luminance would produce specific changes in search latency functions in virtue of affecting visual inhibition. The results of our first two experiments confirmed these predictions: when search was difficult, and produced reaction time results characteristic of serial processing, there was a main effect of adapting luminance and a significant interaction between adapting luminance and the number of display elements. These effects were both reflected in increases in the slopes and the intercepts of average search latency functions when adapting luminance was decreased. When search was easy, and produced pop out effects characteristic of parallel processing, there were no significant effects of adapting luminance on search latency. The third experiment used adapting luminance to further explore the possibility that arrow junctions are detected preattentively. The results suggested that a visual search for such elements involves a substantial serial component, which weighs against the claim that they are detected by low-level vision.

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1. Introduction

Visual search tasks are frequently used to study visual cognition. The primary data obtained in such tasks are search latency functions, which represent the time required to detect the presence or absence of a target as a function of the total number of display elements. Pioneering work on visual search discovered the so-called "pop out" effect: the time to find targets characterized by a unique feature is typically independent of the number of distractor elements in a display, producing a flat search latency function (e.g., Treisman and Gelade, 1980). In contrast, the time to detect a target defined by a unique *combination* of features generally increases with the number of distractor items, producing search latency functions with positive slopes. These results formed the basis for Treisman's feature integration theory of attention, which proposed that the visual features that produced pop out were detected and represented preattentively, and comprised a primitive vocabulary for visual perception (e.g., Treisman, 1985, 1986, ; Treisman and Gelade, 1980; Treisman et al., 1977).

More recent results (e.g., Dehaene, 1989; Enns and Rensink, 1991; Nakayama and Silverman, 1986; Quinlan and Humphreys, 1987; Wolfe et al., 1988) have shown that, in some situations, targets defined by feature combinations can pop out. As this is inconsistent with feature integration theory, new theories of visual search have emerged in which the primary predictors of search latency functions are the similarities between target and nontarget elements (Duncan and Humphreys, 1989; Treisman and Gormican, 1988). On the basis of these new theories, visual cognition researchers are now interested in altering search latency functions by manipulating display element similarity. This requires experimenters to calibrate stimulus similarity (e.g. Treisman, 1991). Unfortunately, these calibration techniques are themselves controversial (e.g., Duncan and Humphreys, 1992).

In contrast to traditional approaches, the experiments reported below were not motivated by existing theories of visual search. Instead, these studies were designed to test a prediction based upon several different computational models of how visual attention can be shifted (Fukushima, 1986; Gerrissen, 1991; Koch and Ullman, 1985; Sandon, 1992). As a result, we succeeded in manipulating search latency in experiments which held stimulus properties constant. The results from this novel paradigm support a major assumption common to these computational models of attention. Furthermore, they provide additional insights into the mechanisms that underlie visual search and visual cognition.

1.1. Inhibition and attention

Several researchers have proposed computational models of the attentional shifts that are required to detect targets in a visual search task (Fukushima, 1986; Gerrissen, 1991; Koch and Ullman, 1985; Sandon, 1992; Grossberg, 1980; LaBerge et al., 1992). While the specific details of these models differ, their general structure is quite similar.

First, these models represent the display being searched as an array of processing units that can adopt different levels of activity. As the search task begins, the activity of each processing unit is a function of the visual distinctiveness of the location that the processor represents (i.e., how different it is in appearance relative to its neighbors). Typically, this measure of distinctiveness is global, in that it is computed across all of the features that characterize the display elements (see, for example, the saliency map described by Koch and Ullman, 1985). Distinctiveness is not defined with respect to individual features (e.g., distinctiveness is not computed for an element's color and orientation separately).

Second, these models describe the attentional "spotlight" used to search for targets as a network that can "examine" the activity of these processors. The network identifies the most active processor (representing the most distinctive location) within the examined region by implementing a winner-take-all (WTA) competition (Feldman and Ballard, 1982). Such a competition is defined by lateral inhibition: each processing unit has an excitatory recurrent connection to itself, and has inhibitory connections to neighboring processing units. The experiments described below used adapting luminance to manipulate these inhibitory mechanisms.

Third, in the context of visual search, the models propose that once the WTA competition has been completed, and the most distinctive location has been identified, the display element at this location is examined to see whether or not it is the target. If it is, search stops. If it is not, activity at this location either decays or is inhibited (e.g., Klein, 1988), and the search for the next most distinctive location in the display occurs via another WTA competition.

This type of model provides a straightforward account of pop out. Targets defined by a unique feature will be identified immediately, independently of the total number of display elements. Such targets will produce high global measures of distinctiveness, because the global measure is sensitive to unique features. As a result a pop out target will win the first WTA competition, which processes all display elements in parallel.

This type of model also provides a straightforward account of search latency functions obtained for targets defined by unique conjunctions of features. When the global measure of distinctiveness is computed, these targets will not be coded as being more distinctive than their neighbors, because the global measure is insensitive to the unique feature combinations. If one assumes slight random variations in the connections that define the WTA competition, then the winner of the first WTA competition in these displays will essentially be selected at random. Repeated WTA competitions will be required until the target is actually detected. Thus, for conjunction targets, the WTA models essentially describe search as random selection without replacement. As a result, search latencies will increase with the number of display elements. As well, the search process should be self-terminating, and accordingly the slope of the search latency function when the target is present should be half the slope of the search latency function when the target is absent.

1.2. Adapting luminance and visual search

While models of the type described above provide neat accounts of extant data, to our knowledge no researcher has used such models to generate novel predictions about search behavior. After noting that lateral inhibition is the mechanism that drives attentional shifts in these models, we realized that in the overall brightness of a display (its level of adapting luminance) should affect search latency functions in human subjects if these models were correct.

It is well known that there is far less inhibition in the visual system under conditions of low adapting luminance than under conditions of high luminance. For instance, when the level of illumination is decreased, the organization of center-surround visual receptive fields are altered: the inhibitory surround becomes less effective (Barlow et al., 1957) and the diameter of the excitatory component increases (Derrington and Lennie, 1982; Ransom-Hogg and Spillmann, 1980; Rohaly and Buchsbaum, 1989). Because of its effect on inhibition, changes in adapting luminance also affect the temporal nature of vision: in general, visual processes are faster in the light. For example, when adapting luminance increases, the critical duration for temporal summation decreases (Matin, 1968; Roufs, 1972). Furthermore, photoreceptor responses decay more slowly in the dark than in the light (Whitten and Brown, 1973).

The research cited above indicates that the spatial and temporal characteristics of retinal visual processing can be greatly affected by levels of adapting luminance. Changes in adapting luminance can also influence less peripheral visual processing. For example, it has been demonstrated that when the level of adapting luminance is decreased, subjects can accurately detect the direction of motion over longer spatial and temporal intervals (Dawson and Di Lollo, 1990). To the extent that attentional shifts are governed by the lateral inhibition in a WTA competition, another complex behavior that should be affected by adapting luminance is visual search.

Consider first the case of a highly distinctive target. In this case, when adapting luminance decreases, the WTA competition should slow down because of the decreased amount of inhibition in the system. However, because of its distinctive nature, the target will still pop out, winning the first WTA competition independently of the number of distractors. Thus, for a target that pops out, there should be no interaction between adapting luminance and the number of display elements – the slope of the search latency function should not be affected by adapting luminance. Consider now the situation in which the target is much less distinctive. In this case, several WTA competitions will (on average) be required to detect it, the number of required competitions increasing with display size. One effect of decreasing adapting luminance would be to slow down each of these competitions, exaggerating the serial nature of this type of search. As a result, one would predict an interaction between adapting luminance and the number of display elements, and that decreases in adapting luminance should increase the slope of search latency functions. Below, we report the results of three visual search experiments that tested these predictions.

2. General method

2.1. Subjects

Each of the experiments collected data from four different subjects. The two authors participated as subjects in every experiment. Two additional naive subjects, who were senior undergraduate students or graduate students in the Department of Psychology at the University of Alberta, were paid to participate in each study. These subjects were unaware of the hypotheses being tested, and were only involved in a single experiment. Only one of the naive subjects had previous experience in a visual search experiment.

2.2. Apparatus

Stimulus presentation was controlled by a Commodore 64 microcomputer. Responses were made on a reaction time key interface of the type described by Wright and Dawson (1988). Subjects signaled the presence of a target by pressing the right key of the interface with their right index finger, and signaled the absence of a target by pressing the left key of the interface with their left index finger. Stimuli were presented on a Commodore color monitor (model 1802); the diagonal size of the monitor's screen was 17° of visual angle (33 cm). Subjects viewed the monitor from a distance of 1.00 m with their head positioned on a chin rest.

Variations in adapting luminance were achieved by inserting neutral density filters between the observer and the monitor. The filters (Wratten gelatin filters No. 96, mounted on 55×65 mm^2 glass slides) were placed in front of the observers eyes in a holder attached to the chin rest. Three adapting luminance conditions were tested, by using a 2.0 log filter in one experimental condition, a 1.0 log filter in a second experimental condition, and no filter in a third control condition.

2.3. Displays

The displays were regular arrays of three sizes: 12 elements $\times$ 12 elements, 8×8, and 4×4. Because the elements used to create these arrays were rectangular in shape (due to rectangular shaped pixels on the 1802 monitor), the overall dimensions of these arrays were rectangular, measuring $7.1° \times 9.4°$, $4.2° \times 6.4°$, and $2.4° \times 3.2°$ respectively. In all displays, the elements were separated (center to center) by 0.78° vertically and by 0.58° horizontally. In each experiment, display elements were presented in white (luminance = 96 cd/m^2 as measured by a spot photometer against a medium gray background (luminance = 61 cd/m^2) with a black fixation cross (luminance = 0.65 cd/m^2) in the center of the display. Fig. 1 illustrates some example stimuli from each of the experiments. In each experiment, displays were constructed from two different elements, for descriptive purposes called elements "A" and "B". These elements were low resolution text elements defined in an 8×8 pixel matrix with dimensions of $0.34° \times 0.40°$. The only difference between experiments was the nature of these display elements. In Experiment I, they were connected and unconnected

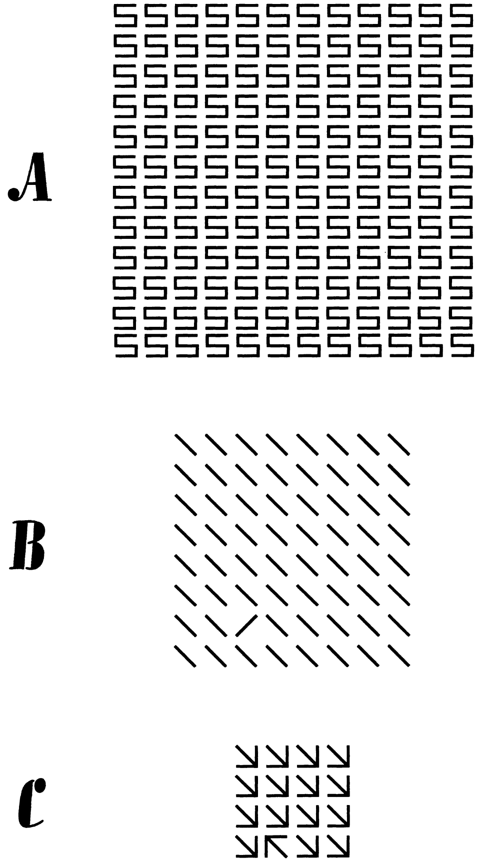

Fig. 1. Sample stimuli used in the experiments; each depicts a display in which the target is present. (A) A 12×12 display constructed from the connected and unconnected figures used in Experiment I. (B) An 8×8 display constructed from the diagonal lines used in Experiment II. (C) A 4×4 display constructed from the arrow junctions used in Experiment III.

figures (see Fig. 1(a)). In Experiment II, they were diagonal lines (see Fig. 1(b)). In Experiment III, they were arrow junctions (see Fig. 1(c)).

With respect to the number of elements that were used to create the stimuli, these displays were not typical of those used to study to visual search. It is much more common to see visual search experiments in which the largest display is composed of 12–25 elements (Bilsky and Wolfe, 1995; Found and Müller, 1996; Müller et al., 1995; Theeuwes and Lucassen, 1993; von Grünau and Dube, 1994; Yantis and Jones, 1991). Indeed, in many visual search studies there are fewer than 10 elements in the largest display (e.g., Bacon and Egeth, 1994; Duncan and Humphreys, 1989; Pashler and Badgio, 1985; Wang et al., 1994; Yantis and Johnson, 1990). In short, the *smallest* display size used in the current study (16 elements) was similar in size to the *largest* display size used in many studies, and was in fact much larger than the largest display size used in many other studies.

We elected to use larger set sizes than those ordinarily studied because of our hypothesis that the slope of the search latency function would be affected by adapting luminance when subjects searched for a conjunction target, but would not be affected by adapting luminance when subjects searched for a pop-out target. If we restricted ourselves to very small number of display elements, then we would be decreasing the likelihood of finding effects that were reflected in differences in slope. This is because the slope of a search latency function reflects the time spent processing an element after an average processing time (i.e., the intercept of the search latency function) has already been included. If only a small number of display elements are used, then reliable (but small) differences in rates of processing elements would be hard to detect. For instance, imagine a situation in which an adapting luminance manipulation increases the rate of per element processing by 1 ms, independently of any effect on the intercept of the search latency function. If our largest display consisted of only 6 elements (as was the case, for instance, for (Wang et al., 1994), then this effect would produce a mere 6 ms increase in latency for the largest display, relative to a control condition. However, by using a much larger number of elements (i.e., 144 as in our largest displays) this effect would produce a 144 ms difference between the experimental and control displays. In other words, by using very large display sizes, we positioned ourselves to detect reliable differences in the rates of element processing, even if these differences were small.

Importantly, while the set sizes that we used were not typical of the visual search literature, they were not unique. We chose the same display sizes as those that were successfully used to study the effects of heterogeneous displays on visual search (Macquistan, 1994). Macquistan found that his stimuli generated results that were predicted by the group scanning model (Treisman and Gormican, 1988). This indicates that while the set sizes that we used were a typical, there is no reason to believe that they tap search mechanisms that are distinct from those studied by other researchers.

2.4. Design

The statistical design of the experiment was as follows: three levels of viewing condition (0.0 filter vs. 1.0 filter vs. 2.0 filter) by three levels of display size (4×4 vs. 8×8 vs. 12×12) by two levels of target type (element A vs. element B) by two levels of distractor type (element A vs. element B). Thus, in half of the trials a target was present, and could be either one of the elements used to create the displays. Within a block of trials, all factors except viewing condition were completely randomized. A single block of trials consisted of 20 repetitions of each combination of display size, target type, and distractor type, making 240 trials in total. Viewing condition was randomized between blocks, under the additional constraint that every three sessions included one block of trials from each viewing condition. This constraint was included in an attempt to equalize practice effects across viewing conditions. Five blocks data were collected from each subject in each viewing condition for a total of 15 sessions.

2.5. Procedure

At the beginning of the experiment, the task was explained to subjects by the experimenter, and subjects were shown demonstration displays. Subjects were instructed to respond as soon as they were aware of the presence or absence of the target figure. It was stressed that speed and accuracy were important, and that subjects should respond as quickly as they possibly could while making fewer than ten percent errors. During a session, subjects were provided trial by trial feedback about accuracy by having a tone sound when an error was made; at the end of the session, subjects were informed about their overall accuracy rate and their average reaction time.

The only source of illumination in the room was from the computer monitor. Each trial began with a black fixation cross ($0.2 \times 0.26°$) presented at the center of the screen. Subjects had been instructed to fixate on this cross. After 1 s, a stimulus array was presented on the monitor while the fixation cross remained. The array remained on the screen until subjects responded, or until ten seconds had elapsed without a response, at which time the trial was ended and a new trial begun. The temporal parameters of the display and the timing of response latencies were controlled by hardware interrupts (Wright and Dawson, 1988).

3. General results

3.1. Data summary

Each subject's data was summarized individually. Search latency functions were determined by computing the mean reaction time for each condition. Only correct responses were used when means were computed. In general, accuracy was very high, averaging over 90%. Thus most of the data points in the graphs presented below are based upon at least 180 observations per subject. The only exception to this occurred in the 12×12 displays in Experiment I, where accuracy was lowered to approximately 80%.

3.2. Experiment I: Hard search

The first experiment created visual search displays from two of the figures originally used to investigate the computational limitations of perceptrons (Minsky and Papert, 1988). These elements, depicted in Fig. 1(a), were selected in a deliberate attempt to produce "hard search", in which search latencies should increase substantially as the number of distractor elements increased. We expected that these two elements would produce hard search on the theoretical grounds that they are impossible to distinguish in terms of their component features, and on the empirical grounds that these different figures do not lead to texture segregation (Julesz, 1981), and do not affect low-level motion correspondence processing (Dawson, 1989).

Table 1 presents the mean reaction times for each of the four subjects who participated in Experiment I. Search latency functions for each subject in each viewing condition were also determined by using linear regression to predict the subject's mean reaction time from the number of elements in a display; these functions are also included in Table 1. Statistical analysis of these data was performed by using multiple linear regression to predict each of the mean reaction times in the table from the target, filter, and display size conditions and their respective interactions. The repeated measures nature of the design was reflected in this analysis by criterion scaling subjects (representing each subject using their overall average reaction time) and using this as a predictor in the regression equation as well (Pedhazur, 1982). The regression equation was highly significant ($R^2 = 0.951$, $F = 153.987$, d.f. = 8, 64, $p < 0.001$). Within the equation, there was a significant effect of subjects ($t = 6.187$, $p < 0.001$), reflecting the fact that some of the subjects were reliably slower than the others (see Table 1). There was also a significant effect of the target condition (present vs. absent, $t = -2.058$, $p < 0.044$); in general, subjects were slower

Table 1
Results of the first experiment for each subject and each condition

Subject	Target	Filter	Reaction time (ms)			Search latency function		
			4 × 4	8 × 8	12 × 12	Slope	Intercept	R^2
MD	Present	0.0	766.44 (16.29)	1319.71 (46.43)	2118.90 (95.19)	10.51	617.14	0.997
		1.0	704.62 (14.93)	1230.57 (44.77)	2086.33 (98.47)	10.79	535.25	1.000
		2.0	796.63 (16.83)	1523.51 (62.89)	2351.32 (104.05)	11.96	663.95	0.978
	Absent	0.0	705.200 (15.49)	1362.95 (48.72)	2562.20 (116.65)	14.56	456.52	0.999
		1.0	703.08 (14.06)	1402.96 (53.49)	2614.23 (118.89)	14.95	456.99	1.000
		2.0	799.84 (17.71)	1663.41 (70.66)	3257.64 (145.26)	19.28	467.71	0.999
MT	Present	0.0	578.38 (8.55)	1020.74 (34.97)	1767.64 (74.04)	9.30	428.17	1.000
		1.0	601.15 (8.98)	1243.84 (50.45)	2139.43 (94.47)	11.93	437.08	0.995
		2.0	667.92 (11.84)	1583.01 (58.59)	3152.54 (129.2)	19.43	350.21	1.000
	Absent	0.0	614.75 (9.27)	1499.52 (29.75)	3196.97 (65.22)	20.28	256.16	0.997
		1.0	677.96 (11.32)	1856.64 (40.49)	3921.01 (72.25)	25.38	256.523	1.000
		2.0	732.80 (13.26)	2530.99 (37.62)	5393.02 (74.84)	36.34	171.96	1.000
IB	Present	0.0	882.49 (18.94)	1522.15 (54.50)	2625.29 (113.74)	13.63	658.69	1.000
		1.0	970.28 (24.89)	1573.78 (58.84)	3062.78 (150.37)	16.58	631.07	0.982
		2.0	1107.00 (23.41)	2075.65 (76.23)	4180.62 (176.27)	24.25	643.96	0.991
	Absent	0.0	1078.21 (24.33)	2891.23 (51.66)	5807.29 (58.39)	36.90	504.05	1.000
		1.0	1192.20 (26.66)	3267.97 (56.43)	6710.79 (88.58)	43.11	505.08	1.000
		2.0	1467.38 (40.78)	4145.35 (72.45)	7524.44 (73.83)	46.80	884.49	0.988
DH	Present	0.0	756.64 (17.52)	1725.17 (78.36)	2711.15 (130.43)	14.97	613.29	0.962
		1.0	785.65 (21.21)	1722.79 (74.30)	2663.26 (140.63)	14.37	650.82	0.960
		2.0	984.65 (30.63)	2132.30 (100.08)	3399.38 (178.89)	18.56	786.58	0.974
	Absent	0.0	1104.44 (31.80)	3103.84 (73.26)	5334.18 (128.36)	32.52	752.83	0.975
		1.0	1161.94 (30.20)	3377.45 (86.20)	5370.49 (143.35)	32.07	909.00	0.940
		2.0	1478.41 (41.10)	3875.56 (93.84)	6033.31 (117.03)	34.71	1204.36	0.940

Mean reaction times in milliseconds are provided; the standard error of each mean is given in parentheses. The slope (in milliseconds per item) and intercept (in milliseconds) are given for the linear regression equation that predicted mean reaction time from the number of display items.

when the target was absent than when it was present. Display size was also a significant predictor of reaction time ($t = 6.801$, $p < 0.001$). An examination of Table 1 indicates that this is because search time became significantly slower as the number of elements in a display increased. [2] All of these effects are expected, because they are consistent with our expectation that the search in Experiment I would be "hard", involving the serial scanning of locations throughout the display.

Of primary interest in this experiment is the fact that two other predictors were also significant contributors to the regression equation that predicted mean reaction time. These were the filter condition ($t = -2.132$, $p < 0.037$) and the interaction between filter condition and display size ($t = 3.841$, $p < 0.001$). An examination of Table 1 reveals that the main effect of filter condition occurs because as the strength of the filter was increased (causing a decrease in adapting luminance), reaction time became slower. The interaction between filter condition and display size reflects the fact that the effect of display size became stronger as adapting luminance decreased.

A general sense of these significant effects involving the filter manipulation can be obtained by recasting the data from Table 1 into a set of average search latency functions. To do this, we averaged the data across subjects, weighting subject means by their associated response accuracy. Linear regression was then used to compute the equation for each of these averaged search latency functions; each of these equations accounted for almost all of the variance in the data being predicted (the smallest R^2 was 0.992). The results of these regressions are graphed in Fig. 2; the actual regression equations that we obtained are provided in the figure legends. An examination of these equations, and of the lines that they produce, reveal a "fanlike" distribution of the search latency functions. As the filter strength is increased, there are increases in both the intercepts and the slopes of the equations. It is these increases in processing time that are reflected in the significant main effect of filter condition, and the significant interaction between filter condition and display size.

In sum, Experiment I revealed significant effects that are consistent with standard results when search is "hard". It also revealed significant effects of adapting luminance on reaction time; these effects are reflected in changes in both the slope and the intercept of search latency functions. These results were predicted from the assumption that visual search is mediated by attentional shifts that are implemented by WTA competitions.

3.3. Experiment II: Pop out

The second experiment attempted to investigate the effect of the neutral density filters on stimuli that produced pop out. Stimuli were defined by two different diagonally-oriented line segments of equal length (e.g., Fig. 1(b)). These stimuli were

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[2] In the psychophysical design of the experiments reported in this paper, the statistical significance of differences between means in the tables is revealed in the context of their standard errors. If the value of the higher mean minus its standard error is still higher than the value of the lower mean plus its standard error, then the two means differ by at least two standard deviations.

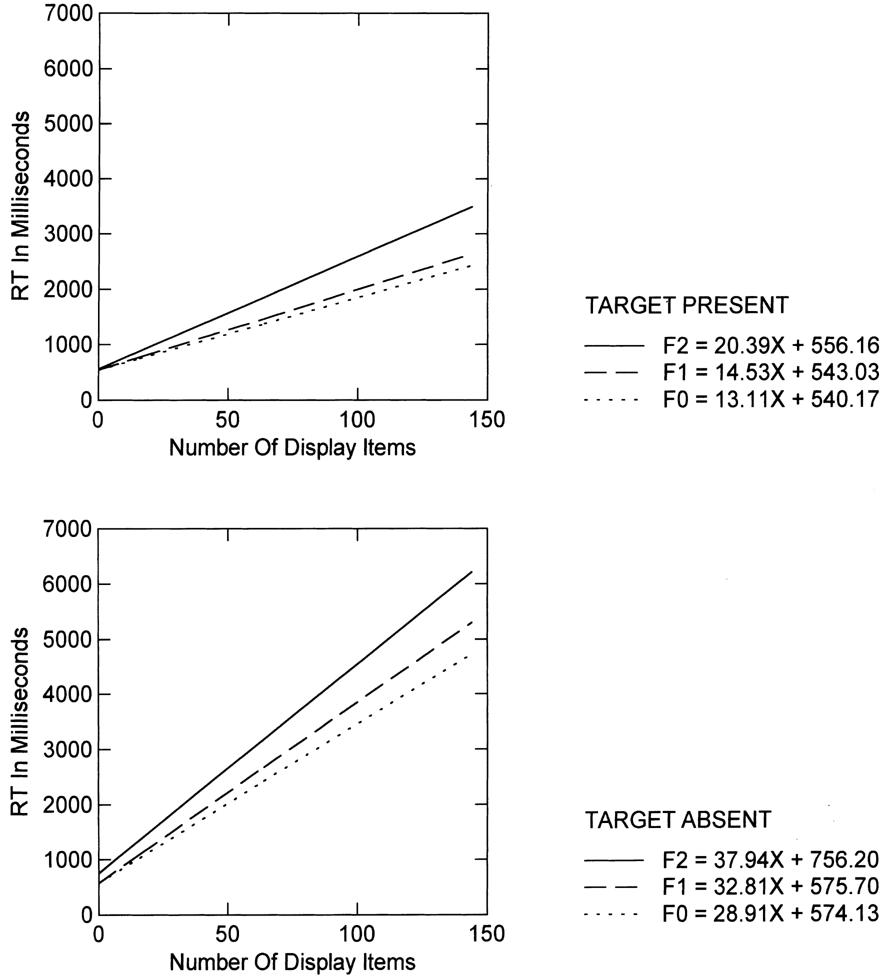

Fig. 2. Regression equations for Experiment I that predicted average reaction time from the number of display elements for each filter condition. Target present equations are at the top of the figure, target absent equations are at the bottom.

selected because of the well-documented finding that differences in orientation produce flat search latency functions (e.g., Treisman, 1986).

Table 2 presents the mean reaction times and the search latency functions obtained for each subject and each condition. In the target-present conditions, it can be seen that all of the search latency functions have a very flat slope, consistent with the notion that targets were popping out. As well, response times to detect the presence of a target were much faster than those obtained in Experiment I. The slopes of the target-absent search latency functions are increasing, suggesting that some serial processing might have been undertaken for these displays, a result consistent with

Table 2
Results of the second experiment for each subject and each condition

Subject	Target	Filter	Reaction time (ms)			Search latency function		
			4 × 4	8 × 8	12 × 12	Slope	Intercept	R^2
MD	Present	0.0	349.52 (3.06)	358.78 (3.91)	368.62 (3.11)	0.147	348.03	0.969
		1.0	359.10 (3.10)	365.72 (3.52)	376.66 (3.74)	0.137	356.92	1.000
		2.0	380.51 (2.94)	387.21 (3.61)	401.68 (3.80)	0.167	377.33	0.991
	Absent	0.0	397.14 (3.89)	398.59 (3.36)	416.34 (4.25)	0.157	392.28	0.952
		1.0	401.15 (3.82)	405.77 (3.36)	433.87 (4.21)	0.265	393.78	0.969
		2.0	417.06 (3.40)	453.09 (5.18)	466.13 (5.05)	0.361	418.481	0.918
MT	Present	0.0	348.62 (2.32)	353.70 (2.64)	365.66 (2.87)	0.135	345.93	0.985
		1.0	367.15 (2.74)	366.94 (2.68)	379.81 (3.48)	0.105	363.44	0.923
		2.0	403.47 (4.34)	413.71 (3.70)	432.93 (4.28)	0.231	399.44	1.000
	Absent	0.0	328.03 (3.68)	337.39 (2.96)	350.06 (3.65)	0.171	325.75	0.998
		1.0	335.18 (2.58)	342.23 (3.02)	349.50 (3.43)	0.110	334.11	0.991
		2.0	386.55 (3.47)	425.69 (3.96)	465.05 (5.95)	0.601	380.90	0.990
KS	Present	0.0	472.83 (5.13)	482.91 (5.09)	513.33 (7.95)	0.323	465.58	0.962
		1.0	478.41 (5.88)	488.80 (6.32)	517.29 (9.42)	0.309	471.75	0.972
		2.0	539.64 (9.8)	536.08 (8.61)	575.43 (7.25)	0.301	527.89	0.895
	Absent	0.0	512.88 (8.79)	599.16 (9.34)	687.84 (9.51)	1.34	499.87	0.991
		1.0	517.11 (6.69)	628.08 (9.57)	756.33 (13.05)	1.84	496.32	0.995
		2.0	558.92 (7.99)	697.77 (12.41)	866.55 (15.03)	2.37	530.53	0.985
MM	Present	0.0	393.94 (5.66)	387.10 (4.24)	395.88 (4.67)	0.03	390.45	0.348
		1.0	404.92 (4.80)	413.23 (5.08)	419.68 (4.94)	0.11	404.26	0.977
		2.0	428.82 (4.74)	425.57 (4.91)	438.34 (5.45)	0.08	424.71	0.809
	Absent	0.0	387.50 (6.40)	404.96 (7.90)	393.22 (5.43)	0.03	393.35	0.183
		1.0	399.67 (6.82)	421.96 (6.90)	415.78 (6.88)	0.105	404.62	0.591
		2.0	426.18 (6.74)	439.39 (6.70)	442.37 (6.45)	0.117	427.22	0.881

Mean reaction times in milliseconds are provided; the standard error of each mean is given in parentheses. The slope (in milliseconds per item) and intercept (in milliseconds) are given for the linear regression equation that predicted mean reaction time from the number of display items.

other pop out experiments (e.g., Treisman, 1991; Treisman and Gelade, 1980). However, these slopes are still many times flatter than those obtained in the first experiment.

Statistical analysis of the means provided in Table 2 was accomplished by using the same multiple linear regression approach that was used in Experiment I. Once again, the regression equation that predicted the mean reaction times given in the table from a set of independent variables and their interactions was highly significant ($R^2 = 0.990$, $F = 887.576$, d.f. = 8, 64, $p < 0.001$). However, in contrast to the results of Experiment I, there was only one significant contributor to this equation: the criterion scaled subject variable ($t = 24.467$, $p < 0.001$). Importantly, neither filter condition ($t = -1.062$, $p < 0.292$) nor the interaction between filter condition and display size ($t = 1.809$, $p < 0.75$) were statistically significant contributors to the overall regression equation.

A graphical sense of these statistical results is revealed in Fig. 3, which presents the search latency functions that we determined by using linear regression to predict

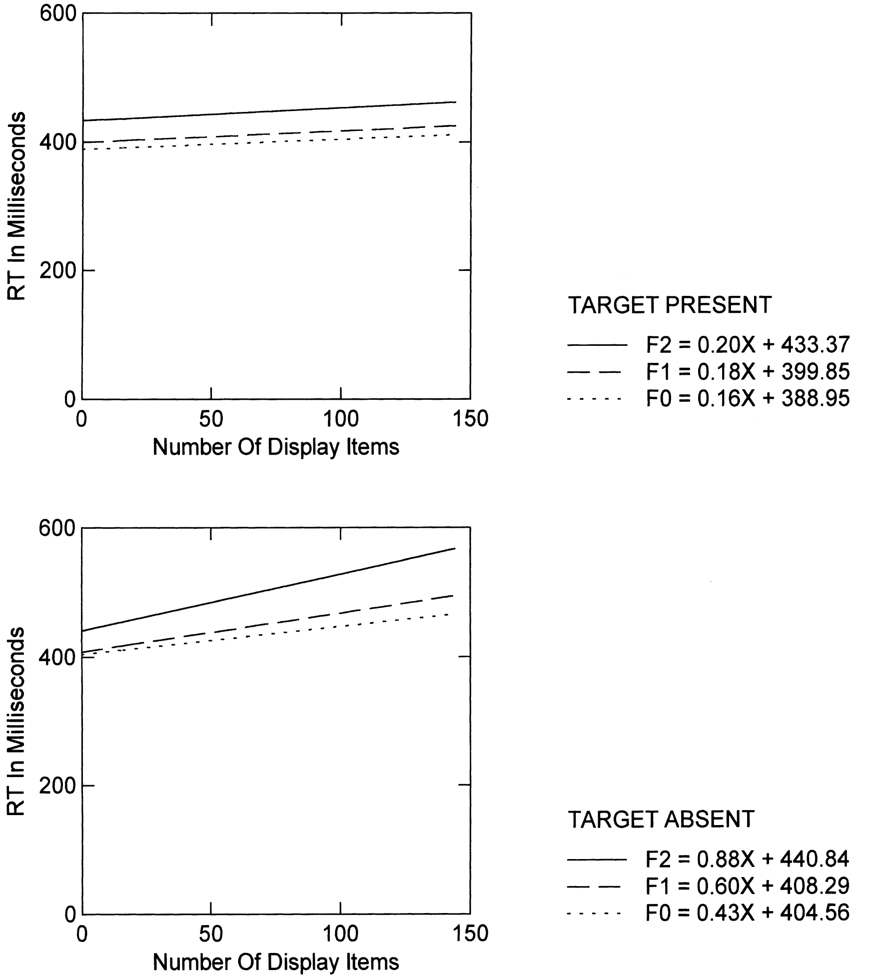

Fig. 3. Regression equations for Experiment II that predicted average reaction time from the number of display elements for each filter condition. Target present equations are at the top of the figure, target absent equations are at the bottom.

the mean reaction time (a weighted average across subjects) from display size for each filter and target condition. Once again, these equations provided an excellent fit to the data (the smallest R^2 was 0.929). In general, these search latency functions are consistent with what one would expect to find in an "easy" search experiment (i.e., one in which the target pops out of the display): they are essentially flat, revealing that the time to detect the target is independent of the number of display items. The regression equations that are provided in Fig. 3 suggest that there is a tendency for the intercepts of the search latency functions to increase as adapting luminance is decreased. It is possible that this tendency might become statistically significant if adapting luminance was decreased even more (though it should be stressed that the 2.0 filter condition provides a very strong decrease in adapting luminance). However, in the current study, an in contrast to the results of Experiment I, no statistically significant effects of adapting luminance on "easy" search were revealed.

These results are quite consistent with the WTA network perspective that motivated our experiments in the first place. From this perspective, the WTA network itself is used to shift attention, and adapting luminance is presumed to affect the inhibitory connections within this network. In a pop out display, by definition, attentional shifts are not required to find the target – so the WTA network would not be involved. If adapting luminance affected the mechanisms that shifted attention, but did not affect the mechanisms for processing targets within the "attentional spotlight", then one would expect exactly the same pattern of results that we discovered in Experiment II.

3.4. Experiment III: Arrow junctions

With the advent of attentional engagement theory (Duncan and Humphreys, 1989), many visual search researchers have shifted their theoretical emphasis from a sharp distinction between serial and parallel processing to a continuum ranging from hard to easy search. For example, Enns and Rensink (1991) used attentional engagement theory to motivate their investigation of search for particular arrangements of line segments. They found that some arrangements of lines led to fast or "easy" visual search, behaving much more like pop out stimuli than conjunction stimuli, and proposed that some of these line arrangements are detected by parallel processes.

Our third experiment investigated the effect of adapting luminance on search for targets in displays defined by arrow junctions (Fig. 1(c)), which Enns and Rensink (1991), Experiment 2A had found to produce fast search. Our methodology serves as a generalization of that used by Enns and Rensink in two respects: First, in their experiment, subjects knew the target's identity beforehand; in our experiment, subjects did not know a priori what the target would be, but searched instead for an odd man out. Second, in their experiment, a very small number of display elements (2, 6, or 12) were used; in our experiment, the number of display elements ranged from 16 to 144. The purpose of this third experiment was to further investigate the possibility that arrow junctions are detected by parallel processes. If this is true, then one would expect patterns of search latency functions similar to those observed in Experiment II. However, if these stimuli require serial processing, then one would expect fan-like patterns of search latency functions like those observed in Experiment I.

Table 3 presents the average reaction times and the search latency functions obtained from the four subjects who participated in this experiment. Somewhat consistent with the interpretation of Enns and Rensink (1991), search for arrow junctions was much easier than the search for connected/unconnected figures in Experiment I. In general, subjects were much faster in this experiment than in Experiment I, although they were not as fast in this experiment as they were when stimuli popped

Table 3
Results of the third experiment for each subject and each condition

Subject	Target	Filter	Reaction time (ms)			Search latency function		
			4 × 4	8 × 8	12 × 12	Slope	Intercept	R^2
MD	Present	0.0	455.99 (7.17)	509.80 (9.09)	608.63 (14.03)	1.20	435.44	1.000
		1.0	462.56 (6.42)	540.06 (9.88)	671.18 (18.00)	1.63	436.17	1.000
		2.0	516.68 (8.37)	625.18 (13.52)	877.30 (30.98)	2.85	460.15	0.997
	Absent	0.0	559.65 (8.51)	753.08 (17.32)	896.47 (18.72)	2.55	546.31	0.897
		1.0	556.36 (8.65)	814.41 (18.40)	1024.36 (22.38)	3.55	533.24	0.919
		2.0	627.04 (9.66)	1081.70 (28.34)	1257.64 (28.86)	4.65	641.72	0.924
MT	Present	0.0	456.75 (4.89)	501.52 (7.47)	572.01 (14.34)	0.90	443.01	1.000
		1.0	447.78 (3.56)	513.20 (6.50)	606.15 (11.43)	1.23	430.57	0.999
		2.0	526.34 (5.36)	651.55 (10.36)	864.12 (21.36)	2.64	483.49	1.000
	Absent	0.0	443.36 (5.48)	555.36 (7.74)	755.02 (16.92)	2.44	402.31	1.000
		1.0	452.64 (3.61)	574.27 (7.36)	775.79 (13.65)	2.52	412.44	1.000
		2.0	537.76 (6.62)	807.91 (12.09)	1310.94 (23.25)	6.07	432.63	0.998
LP	Present	0.0	460.97 (8.76)	522.97 (11.80)	643.95 (18.35)	1.44	435.26	0.997
		1.0	474.33 (8.46)	503.76 (9.18)	673.76 (18.09)	1.62	429.96	0.884
		2.0	493.05 (7.96)	573.73 (9.68)	773.66 (21.81)	2.22	447.45	0.995
	Absent	0.0	489.23 (10.20)	697.11 (9.99)	1039.26 (20.87)	4.30	421.17	1.000
		1.0	486.45 (9.28)	738.42 (12.43)	1030.07 (20.44)	4.19	439.12	0.980
		2.0	516.13 (9.23)	833.59 (16.40)	1186.37 (24.97)	5.15	460.69	0.975
TG	Present	0.0	447.34 (6.93)	533.39 (9.57)	675.27 (22.54)	1.78	419.10	1.000
		1.0	453.28 (5.15)	525.28 (8.39)	657.49 (15.15)	1.60	425.90	1.000
		2.0	540.35 (6.95)	701.80 (15.73)	1068.86 (39.46)	4.18	458.54	0.997
	Absent	0.0	504.87 (8.53)	666.23 (14.99)	830.66 (24.89)	2.50	480.94	0.962
		1.0	494.47 (5.44)	657.08 (10.55)	754.17 (12.48)	1.95	489.96	0.959
		2.0	539.51 (6.06)	1056.53 (17.76)	2072.60 (51.92)	12.05	323.06	0.999

Mean reaction times in milliseconds are provided; the standard error of each mean is given in parentheses. The slope (in milliseconds per item) and intercept (in milliseconds) are given for the linear regression equation that predicted mean reaction time from the number of display items.

out in Experiment II. Furthermore, the slopes of search latency functions in this experiment were shallower than those obtained in Experiment I.

Statistical analysis of the means provided in Table 3 was accomplished by using the same multiple linear regression approach that was used in the previous experiments. Once again, the regression equation that predicted the mean reaction times given in the table from a set of independent variables and their interactions was highly significant ($R^2 = 0.974$, $F = 298.783$, d.f. = 8, 64, $p < 0.001$). Within this regression equation, there were only three significant contributing predictors. The first, as was the case with the previous two experiments, was the criterion scaled subject variable ($t = 8.428$, $p < 0.001$), reflecting reliable differences between subjects in terms of their average response time. The second was the number of display items ($t = 3.570$, $p < 0.001$). As can be seen from Table 3, increases in the number of display elements produced significant increases in reaction time. The third was a significant interaction between the filter condition and the number of display items ($t = 4.283$,

$p < 0.001$). The three-way interaction between filter condition, number of display items, and the presence vs. absence of the target approached, but did not achieve, statistical significance ($t = -1.819$, $p < 0.074$).

A graphical sense of these statistical results is revealed in Fig. 4, which presents the search latency functions that we determined by using linear regression to predict the mean reaction time (a weighted average across subjects) from display size for each filter and target condition. These equations provided an excellent fit to the data (the smallest R^2 was 0.980). This figure clearly indicates that the effect of the neutral density filters in this experiment are much more similar to the effects found in Exper-

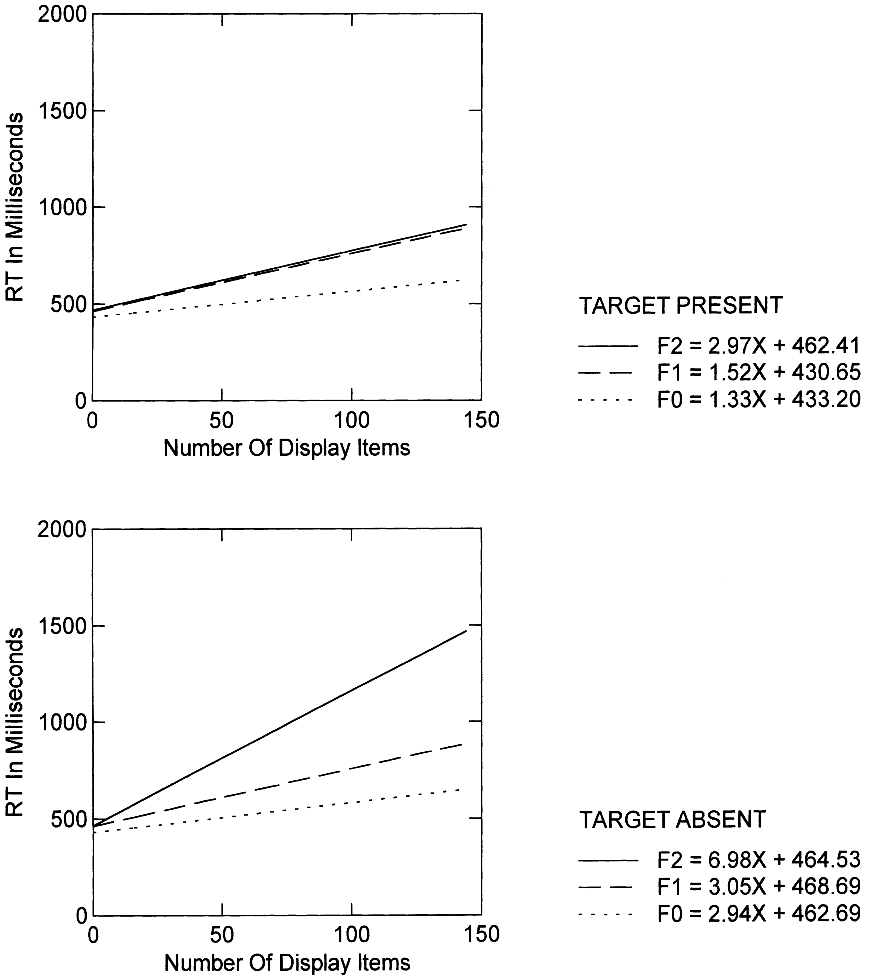

Fig. 4. Regression equations for Experiment III that predicted average reaction time from the number of display elements for each filter condition. Target present equations are at the top of the figure, target absent equations are at the bottom.

iment I than to those found in Experiment II. First, the neutral density filters produced substantial increases in the slopes of the search latency functions, resulting in a "fanlike" appearance of the search latency functions, which explains the significant interaction between filter condition and display size. Second, the neutral density filters produced small increases in the intercepts of the regression equations. Third, the slopes of each target-present function is approximately half of the slope of the corresponding target-absent function. The fact that there is a more marked "fanning" of the target absent functions than of the target present functions explains why the three-way interaction between target, filter, and display size conditions approached significance.

These observations are consistent with the interpretation that search for arrow junctions involves a substantial serial component that was amplified in our experiment by using larger displays and by manipulating adapting luminance. These results are not what one would expect if arrow junctions are detected by low-level vision, which is typically characterized by parallel computations throughout the visual field (e.g., Marr, 1982; Ullman, 1984). However, these results also confirm the findings of Enns and Rensink (1991) that search for arrow junctions is easier than search for other types of feature conjunctions. It is obvious from a comparison of the results of the three experiments that while subjects found the arrow junctions harder to search than the oriented lines, they were much easier to search than the connected/unconnected figures.

4. General discussion

Computational models of attentional processing typically view the "attentional spotlight" as a winner-take-all network whose focus can be shifted serially about a display if required. As a result, lateral inhibition is assumed in these models to be an important determinant of visual search. On the basis of this assumption, we predicted that changes in adapting luminance would produce specific changes in search latency functions in virtue of affecting visual inhibition. The results of our first two experiments confirmed these predictions: When search is difficult, and produces reaction time results characteristic of serial processing, decreasing levels of adapting luminance produced significant effects on search latency; in particular, a significant main effect of filter condition and a significant interaction between filter condition and display size. These effects are reflected as increases in both the slopes and the intercepts of average search latency functions. When search is easy, and produces pop out effects characteristic of parallel processing, there were no significant effects of adapting luminance on search latency. This is consistent with the notion that adapting luminance affects the mechanisms that shifts attention, but does not affect the processing of stimuli within the attentional "spotlight". The third experiment used adapting luminance to further explore the possibility that arrow junctions are detected preattentively. The results suggested that a visual search for such elements involves a substantial serial component, which weighs against the claim that they are detected by low-level vision.

4.1. Relation to other manipulations of brightness

Before considering our results in the context of some of the major theories of visual search, it is instructive to compare and contrast them with those found in other studies that have studied a variety of manipulations of stimulus brightness.

In the studies that were reported above, neutral density filters were used to manipulate overall stimulus luminance because these filters do not affect the relative contrast of elements in a display. One previous study (Pashler and Badgio, 1985) has examined visual search from almost the opposite perspective. Pashler and Badgio manipulated stimulus quality by changing the brightness of individual elements in the display. This kind of manipulation clearly changes the relative contrast of elements, but because it is localized to a very small part of the total visual display (i.e., a small number of elements against a large background which is itself unchanged), it produces relatively small changes in overall display luminance. In a visual search task in which targets did not pop out, Pashler and Badgio found that decreases in item contrast increased the intercepts of search latency functions, but did not affect the slopes of these functions. This is quite different from our results in Experiment I.

However, the fact that manipulations of display luminance can produce different effects than manipulations of element contrast is not surprising. Indeed, a similar dissociation between luminance and contrast effects has been revealed in studies of other perceptual processes. For instance, Dawson and Di Lollo (1990) found that manipulations of display luminance had significant effects on both the temporal and spatial limits of motion perception. However, they found that these limits were unaffected by changes of the brightness of the dots used to create their displays, a finding in agreement with several other studies that had observed the relative insensitivity of motion perception to stimulus contrast (Barlow and Hill, 1963; Braddick, 1973; Campbell and Maffei, 1981). Dawson and Di Lollo accounted for their results by arguing that while there is evidence that adapting luminance can reorganize the receptive fields (i.e., decrease the size of inhibitory surrounds) of cells early in the visual pathway (Barlow and Hill, 1963; Braddick, 1973; Campbell and Maffei, 1981; Derrington and Lennie, 1982; Ransom-Hogg and Spillmann, 1980; Rohaly and Buchsbaum, 1989), there is no evidence that stimulus contrast has a similar effect. Dawson and Di Lollo successfully created a computer simulation of motion perception that dissociated luminance and contrast effects. This was accomplished by varying properties of the model (i.e., temporal and spatial filters analogous to receptive fields) as a function of adapting luminance, and by varying properties of the stimuli (i.e., dot intensity) as a function of contrast.

Is there any reason to believe that the different effects of luminance and contrast on visual search is related to their effects on different mechanisms? It has long been known that if a single element in a visual display is momentarily brightened, that attention will be drawn to this item, and it will pop out (e.g., Yantis and Hillstrom, 1994; Yantis and Johnson, 1990; Yantis and Jonides, 1984). However, some recent results have indicated that this kind of effect is quite complex. In particular, it only appears to occur when the brightness of an item within the current focus of attention is changed; if the item is outside the focus of attention when it is brightened, it does not draw attention to it (Theeuwes, 1991; Theeuwes, 1995). There is also some evidence suggesting that this automatic capture of attention can be mitigated by using conditions that force subjects to search for features instead of whole elements (Bacon and Egeth, 1994).

Taken all together, these results suggest that manipulations of element contrast affects the processing of elements that are already undergoing some sort of attentional processing. They are mute, however, with respect to the issue of whether contrast affects the actual shifting of attention. In fact, given that WTA mechanisms are at the core of most models of attention shifting, that these mechanisms depend upon inhibition, and that inhibition is known to be affected by adapting luminance, it is quite possible that luminance affects the shifts of attention, and that contrast effects only emerge once processing within the "attentional spotlight" has commenced. One area of promise for future research is the study of visual attention in experiments that covary both luminance and contrast, and which might be able to dissociate between processing before and after shifts of attention.

The current studies were motivated by models of the shift of attention, and were not motivated directly by theories of visual search. However, these theories are the linchpin of the psychological literature on search. We now turn to considering the results of our three experiments in the context of some of the major models of visual search.

4.2. Relation to group scanning theory

Group scanning theory (Treisman and Gormican, 1988), which represents a major elaboration of feature integration theory, could provide a very natural account of the results of all three of our experiments. According to the group scanning model, the span of the attentional "spotlight" depends upon the relative discriminability of targets from distractors. When this discriminability is very high, the attentional spotlight spans the entire display, and visual search is parallel. As this discriminability becomes lower, the attentional spotlight must narrow, and serial shifts of attention may be required to detect a target.

If one takes featural overlap as a basic index of discriminability, then it is clear that the diagonal lines used in Experiment II have almost no overlap, and should be highly discriminable. The connected/unconnected figures used in Experiment I share all of their first order (line segment) features, and should be very difficult to discriminate. The two arrow junctions from Experiment III share a single feature (the diagonal line), and thus should have some intermediate level of discriminability. Thus, the group scanning model would likely predict flat search latency functions in Experiment II (at least when targets were present), steep search latency functions in Experiment I, and moderately sloped search latency functions in Experiment III. In general, this is indeed what we found.

However, without further elaborating the group scanning model to describe some attentional mechanism, it cannot predict the effects produced by changes in adapting luminance. Of course, it would be relatively straightforward to elaborate the group scanning model by asserting that the spotlight of attention is instantiated in the general manner assumed by the computational models reviewed earlier.

4.3. Relation to guided search

Wolfe (1994) and Wolfe et al. (1989) has observed that in the feature integration model proposed by Treisman and her colleagues (Treisman and Gelade, 1980), information delivered by early feature detection systems has little influence on later visual search processes (i.e., attentional shifts) if pop out does not occur. Wolfe notes that this is a shortcoming, because a great deal of the information detected by early, parallel processing can be used to constrain the locations that serial processes search when a target is sought. In particular, Wolfe argues that this information can be used to identify locations which have a high probability of containing a target. As a result visual search could be made more efficient (relative to feature integration theory) by taking this kind of information into account.

Wolfe (1994) and Wolfe et al. (1989) has proposed a model of visual search that serves as an alternative to the feature integration model because it uses information detected early and in parallel to guide later serial searching of a display. The most recent version of this model, Guided Search 2.0, filters a stimulus through a number of input channels that are sensitive to specific properties such as color and orientation. The output of these channels is then used to create activity in a feature map for each property. This activity measures how unusual a location is in the context of its neighboring locations: the more dissimilar a location is from its neighbors, the higher is its activity in the feature map. Top-down goals can affect feature map activity as well, by using task goals to select one of the used to construct a feature map channels (e.g., the "red" or "green" channel feeding into the "color feature map"). The activities of all of the feature maps are then summed together to create an activation map. This map is used to guide attention to specific locations in the display. Attention is drawn to the location that corresponds to the highest level of activation in the activation map. If the target is not found at this location, this "peak" of activity in the activation map is inhibited, and attention shifts to the location that has the next highest level of activity (in the original activation map). Wolfe has shown that this model provides a very nice account of visual search results, and has used it to predict visual search phenomena that are not consistent with feature integration theory.

At first glance, the guided search model seems very similar to the WTA models of attentional shifts that were described previously. Both types of models agree that attention should be shifted to the most active location in a visual array. However, while the WTA models use inhibitory signals to identify the most active location by turning all other locations off, no such processing is carried out in the guided search model. Indeed, Wolfe has not specified precisely how attention is shifted in his model. "It is probably a mistake to think of attention 'moving' from location to location in some strict analogy with eye movements or mental imagery. More plausibly, it is deployed at location x, then disengaged from x, and redeployed at y without necessarily traversing intermediate points" (Wolfe, 1994),

p. 238. However, Wolfe does not provide any details about the particular mechanisms of attentional deployment.

This is unfortunate, because such details are required if the guided search model is to account for the effects of luminance that have been described in the current manuscript. In the guided search model, attentional shifts do not occur until the activation map has been created. Because of this, the guided search model does account for the significant interaction between adapting luminance and display size (i.e., the change of slopes of the search latency functions) in Experiments I and III. If the activation map has already been created, then why would deploying attention from one peak in the map to another be slower in the dark than in the light? Without saying precisely what attentional deployment is, this question cannot be answered.

Of course, this is not to say that our results are inconsistent with the guided search model, because it could easily be elaborated in a number of different ways to account for the effects of adapting luminance that we have observed. The first elaboration would simply be to explore the possibility that the shifting of attention from one location in the activation map to another is mediated by a WTA model. For instance, this could be accomplished by using the activation map as input to a WTA network; the output of this network – the winner of the competition between locations – would be the location to which attention is deployed. Luminance effects on visual search for targets that do not pop out could be accounted for by appealing to changes of the inhibitory connections in the WTA network.

A second, and more intriguing, elaboration of the guided search model could emphasize the mechanisms of attentional disengagement. In the current version of the model, when attention is disengaged from a location, the location is "marked" so that it is not returned to during that search trial. This is accomplished by setting that location's activation in the activation map to an arbitrarily low value (Wolfe, 1994), p. 209. This is proposed as being analogous to the process called *inhibition of return* (Posner and Cohen, 1984; Posner et al., 1985). While there is general agreement in the literature about the existence of inhibition of return, there is little consensus about why or how it occurs for discussion, see (Wright and Richard, 1997; Wright and Ward, 1997). However, some researchers have proposed that inhibition of return is the result of a preattentive, sensory event which (in part) initiates an inhibitory signal which is initially masked by a co-occurring excitatory signal, but which affects processing later (Posner and Cohen, 1984). This account is consistent with recent findings that inhibition of return can occur at multiple locations in a display (Wright and Richard, 1997). Now, a preattentive inhibitory event is exactly the kind of signal that we would expect to be disrupted by decreases in adapting luminance (see also Dawson and Di Lollo, 1990). So, it is possible that explicit inhibitory mechanisms for inhibition of return could be added to the guided search model. When adapting luminance is decreased, inhibition of return is less extreme, and this results in a slowing of shifts of attention (and resulting increases in search latency function slopes) either because attentional disengagement at one location is slowed, or because a previously searched location is not inhibited, and is thus searched more than once.

4.4. Relation to attentional engagement theory

A more radical departure from feature integration theory has been attentional engagement theory (Duncan and Humphreys, 1989). In this model, the first stage of a visual search task is the parallel segmentation and analysis of the image. Then, the structural units defined by this first stage of processing compete for selection into a visual short-term memory (VSTM). Access to VSTM depends upon two factors. First, a display element is more likely to enter VSTM depending upon its match to an attentional template for the target which is guiding the search process. Second, entire groups of elements can be selected or rejected together if they are linked by perceptual grouping (e.g., with a homogenous set of distractors, all nontargets may be treated as a single group on the basis of similar appearance). This is because when objects are linked, if the likelihood of the entry of one of these objects to VSTM is altered, then this change in likelihood is passed on to the other members of the group.

According to attentional engagement theory, the difficulty of visual search depends upon the ease with which a target can gain entry into VSTM. This in term depends upon the difference between the likelihood of a target entering VSTM and the likelihood of a nontarget entering VSTM (Duncan and Humphreys, 1992). Typically, this difference is viewed as a function of target–nontarget similarity, and as a function of nontarget–nontarget similarity.

The key point of the results that we report above, in terms of attentional engagement theory, is that search difficulty can be manipulated while both target–nontarget and nontarget–nontarget similarities are held constant: within an experiment, stimulus properties were held constant across the different adapting luminance conditions. Thus, the increased difficulty in finding the target under dark viewing conditions in Experiments I and III suggests that adapting luminance has direct effects on the mechanism that selects information for entry into VSTM.

We hypothesize that access to VSTM is best considered as a competitive interaction between spreading suppression and template matching, and that WTA is the mechanism that mediates this interaction. With this mechanism, each element would have an excitatory signal to itself that was equal to its match to the current template, and would send an inhibitory signal to its neighbors that was also a function of this match. Winners of local WTA competitions would gain access to VSTM, which is assumed to have small capacity. If the target is not detected among those elements that are in VSTM, then VSTM must be "flushed", and new items must compete for entry. From this perspective, the effect adapting luminance is to slow down the WTA competition between template matching and spreading suppression. This will enhance the serial nature of search for "hard" stimuli, as VSTM will likely have to be filled several times before the target is identified.

Our only concern with this account rests with a key design feature that differentiates attentional engagement theory from feature integration theory: in the former, the objects that compete for entry into VSTM have had a great deal of analysis, and might already have semantic descriptions attached to them (Duncan and Humphreys, 1989). This would suggest that competition for entry into VSTM is a much more central process than is the capture of attention in feature integration theory. Although it is not impossible, we would suspect that changes in adapting luminance would be more likely to affect early processing than late processing, and thus are uncomfortable with the claim that adapting luminance affects a post-semantic selectional process.

5. Conclusion

Current versions of feature integration theory and attentional engagement theory do not predict the results of the three experiments that we reported above. This is because these theories have been relatively silent with respect to specific claims about the mechanisms underlying visual search and visual attention. Our results point to one psychophysical method that can be used to directly manipulate these attentional mechanisms while holding stimulus properties constant. Our hope is that researchers will soon turn to the development of other paradigms that are similar in spirit, with the ultimate goal of providing a rigorous account of the mechanisms that mediate visual attention and visual search.

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