CHAPTER ONE

Visual Search

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Loosely following William James, we can assert that everyone knows that visual search tasks are because everyone does them all the time. Visual search tasks are those tasks where one looks for something. This chapter will concentrate on search tasks where the object is visible in the current field of view. Real world examples include search for tumors or other critical information in x-rays, search for the right piece of a jigsaw puzzle, or search for the correct key on the keyboard when you are still in the "hunt and peck" stage of typing. Other searches involve eye movements, a topic covered in Hoffman's chapter in this volume.

In the lab, a visual search task might look something like Fig. 1.1. If you fixate on the central asterisk in Fig. 1.1, you will probably find an "X" immediately. It seems to "pop out" of the display. However, if you are asked to find the letter "T", you may not see it until some sort of additional processing is performed. Assuming that you maintained fixation, the retinal image did not change. Your attention to the "T" changed your ability to identify it as a "T". Processing all items at once ("in parallel") provides enough information to allow us to differentiate an "X" from an "L". However, the need for some sort of covert deployment of attention in series from letter to letter in the search for the "T" indicates that we cannot fully process all of the visual stimuli in our field of view at one time (e.g. Tsotsos, 1990). Similar limitations appear in many places in cognitive processing.

It is important to distinguish covert deployment of attention from movements of the eyes. If you fixate on the asterisk in Fig. 1.2, you will find
that, not only does the "T" not pop out, it cannot be identified until it is foveated. It is hidden from the viewer by the limitations of peripheral visual processing. You can identify the stimuli in Fig. 1.1 while fixating the central asterisk. This is not to say that you did not move your eyes—only that you did not need to move your eyes. For most of the experiments discussed in this chapter, eye movements were uncontrolled. While interesting, eye movements are probably not the determining factor in visual searches of the sort discussed in this review—those with relatively large items spaced fairly widely to limit peripheral crowding effects (Levi, Klein, & Aitsebaomo, 1985). For instance, when Klein & Farrell (1989) and Zelinsky (1993), using stimuli of this sort, had participants perform the search tasks with and without overt eye movements, they obtained the same pattern of reaction time (RT) data regardless of the presence or absence of eye movements. The eye movements were not random. They simply did not constrain the RTs even though eye movements and attentional deployments are intimately related (Hoffman & Subramaniam, 1995; Khurana & Kowler, 1987; Kowler, Anderson, Dosher, & Blaser, 1995).

The basic organization of this chapter is as follows: first, some paradigmatic issues are discussed. The second section is devoted to describing the properties of preattentive processing; the processing of stimuli that occurs before attention is deployed to an item in a search task. The third section discusses the use of preattentive information by subsequent processes. A number of topics, relevant to visual search, are discussed elsewhere in this volume and not here. For example, see Luck’s chapter for coverage of the electrophysiological literature.

SECTION I: THE BASIC PARADIGM

In a standard visual search, subjects look for a target item among some number of distractor items. The total number of items in the display is known as the set size. On some percentage of the trials, typically 50%, a target is present. On the other trials, only distractors are presented. Subjects make one response to indicate that they have found a target and another response to indicate that no target has been found. The two dependent measures that are most commonly studied are reaction time (RT) and accuracy. In studies where RT is the measure of interest, the display usually remains visible until the subject responds. RT is generally analyzed as a function of set size, producing two functions—one for target present and one for target absent trials. The slopes and the intercepts of these RT x set size functions are used to infer the mechanics of the search.

There are numerous variations on the basic search task. For instance, it can be profitable to have subjects search for any of two or more targets at once (Estes & Taylor, 1966) or to divide attention between two different search tasks (e.g. Braun & Julesz, 1996a, 1996b; Braun & Sagi, 1990a).

Accuracy Methods

In addition to RT experiments, the second major method for studying visual search uses accuracy as the dependent measure (Bergen & Julesz, 1983; Braun & Sagi, 1990b; Eriksen & Spencer, 1961; Sagi & Julesz, 1985; Shiffrin & Gardiner, 1972). In this case, the search stimulus is presented only briefly. It is followed by a mask that is presumed to terminate the search. The stimulus onset asynchrony (SOA) between the onset of the stimulus and that of the mask is varied and accuracy is plotted as a function of SOA (see Fig. 1.3). In a search where many or all items can be processed in a single step, the target can be detected even when the SOA is very short. In a search where each item must be processed in turn (e.g. Ts among Ls), the accuracy data are consistent with the view that one additional item is processed for each 40–50 msec increase in the SOA (Bergen & Julesz, 1983). That is, the
FIG. 13. Easier searches can be performed with high accuracy even when a mask follows a briefly presented search stimulus with a short SOA. Harder search tasks require longer SOAs and may never reach near perfect performance.

Data are consistent with a serial search.1 Accuracy methods are of particular use if one wants to eliminate the possibility of eye movements. A stimulus can be flashed for 50 msec—too short for voluntary eye movements. Nevertheless, the internal representation of that stimulus can be searched until a mask appears several hundred msec later.

Interpreting Search Results

Returning to the RT method, it helps to begin with two extreme cases when considering the analysis of RT \times size slopes. Consider a search for a red item among green distractors. As has been shown many times (e.g. Nagy & Sanchez, 1990), the number of green items makes very little difference. Either red is present or it is not. The resulting RT \times set size slopes have slopes near zero msec/item. The usual inference in the visual search literature is that these results reflect an underlying parallel search. Apparently, all items can be processed at once to a level sufficient to distinguish targets from non-targets. The red item, if present, “pops out” and makes its presence known. In contrast, a search for a S among 2 s will produce target trial slopes of 20–30 msec/item and blank trial slopes of about 40–60 msec/item. Searches yielding this pattern of results are usually called serial searches because the pattern of results is consistent with a random, serial self-terminating search through the items at a rate of one item every 40–60 msec. The logic is as follows: On a target present trial, the target might be the first item visited by attention. It might be the last item or it might be any item in between. On average, attention will need to visit half of the items. On target absent (blank) trials, attention will have to visit all items in order to confirm the absence of the target. As a result, the cost of adding one additional distractor is twice as great for blank trials as for target trials and the resulting slopes of the blank trials should be twice as great (but see Horowitz & Wolfe, 1977).

The distinction between serial and parallel processes has a long history (e.g. Kinchla, 1974; Neisser, 1967; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Sternberg, 1969; see Bundesen, 1996, and Kinchla, 1992, for recent reviews). The notion of a division between parallel and serial visual searches became theoretically prominent when Anne Treisman proposed her original Feature Integration Theory (FIT; Treisman & Gelade, 1980). Treisman's proposal was that many feature searches were parallel searches and that everything else required serial search. Feature searches are searches where the target is distinguished from distractors by a single basic feature like color, size, or motion (the list of basic features will be discussed later). “Everything else” included searches for targets defined by conjunctions of features. For example, in a search for a big red square among small red and big green squares, the target is defined by a conjunction of color and size. Neither the size nor the color feature alone defines the target.

Today, 15 years after the publication of the original FIT, the serial/parallel dichotomy is a useful, but potentially dangerous fiction. The strict form is no longer part of FIT (Treisman, 1993; Treisman & Sato, 1990) and it is explicitly rejected by various other models of visual search (Duncan & Humphreys, 1989; Wolfe, 1994a; Wolfe, Cave, & Franzel, 1989; Humphreys & Muller, 1993; Grossberg, Mingolla, & Ross, 1994). Nevertheless, there is a steady stream of papers that either use the dichotomy as fact or consider the strict form to be a worthy target of new research. In hope of reformulating this aspect of the debate about mechanisms of visual search, the following section presents four reasons why the serial/parallel dichotomy in visual search is deceased and ought to be allowed to rest in peace.

1. Inferring Mechanisms From Slopes is Not That Simple

For more than 20 years, Townsend and others have been warning that RT \times size measures are inadequate to discriminate between underlying parallel and serial mechanisms (Atkinson, Hornigren, & Juola, 1969; Townsend, 1971, 1976, 1990). For example, parallel processing is routinely inferred from shallow target-trial slopes (e.g. 5 msec/item). However, in principle these could be the product of a serial mechanism that processes one item every 10 msec. Further, the pattern of results produced by a serial self-terminating search can also be produced by a variety of limited-capacity
parallel models (e.g., Kinchla, 1974; Ratcliff, 1978; Ward & McClelland, 1989; and see Palmer & McLean, 1995, for a model employing unlimited-capacity processes). A model of this sort (loosely borrowed from Ratcliff, 1978) might look like Fig. 1.4.

The idea of a limited-capacity parallel model is that all items in the display are processed at once. Evidence accumulates at each location for the presence of a target or non-target item. Search terminates when one item crosses the “yes” threshold or when all items cross the “no” threshold. The bell curves in Fig. 1.4 are intended to show the hypothetical distribution of finishing times for target and non-target items. The rate of accumulation is dependent on the amount of the parallel resource that is available. Given a fixed amount of resource, an increase in set size will result in a decrease in the amount of resource per item. This will slow each item’s journey to the threshold, producing an increase in RT with set size. Judicious placement of thresholds can produce the desired 2:1 slope ratios and other hallmarks of serial search. As a result, it is very difficult to distinguish between models with a serial deployment of attention and limited-capacity parallel alternatives on the basis of slope magnitudes or slope ratios alone.²

![Diagram of Limited-Capacity Parallel Model](image)

FIG. 1.4. A limited-capacity parallel model.

²Devotees of the serial deployment of attention, including the author, think that the parallel models have to introduce “a plethora of new threshold and rate parameters” (quote from an anonymous reviewer).

2. “Strict” Serial Search Involves a Number of Unfounded Assumptions

The 2:1 slope ratio prediction relies on the assumption that target trials involve serial search through an average of half the items while blank trials involve search of all items. The blank trial assumption is undoubtedly too strong. First, it requires that search be exhaustive but that no items are ever checked twice (Horowitz & Wolfe, 1997). Second, it makes no provision for errors. Many published “serial” searches have error rates in the 5–10% range. Most of these errors are “misses”, suggesting that the search ended before all items were visited. These factors complicate the 2:1 slope ratio prediction (Chun & Wolfe, 1996).

The strict model also assumes that one item is processed at a time. Several researchers propose that more than one item can be processed in a single attentional “fixation”³ (Gilmore, 1985; Grossberg et al., 1994; Humphreys & Muller, 1993; Humphreys, Quinlan, & Riddoch, 1989; Pashler, 1987; Ross & Mingolla, 1994; Treisman, 1992). Models that propose that search proceeds from group to group (Grossberg et al., 1994) are hybrids, lying between FIT-style models and limited-capacity parallel models (see Section III).

3. The Strict Model Assumes a Fixed “Dwell Time”

Dwell time, the amount of time that attention spends at a location once it is deployed to that location, is an important parameter in attention models. Asserting that target–trial slopes of 5 msec/item reflect parallel search mechanisms assumes that such slopes could not reflect serial mechanisms operating at a rate as fast as one item every 10 msec. It assumes that the dwell time must be longer than 10 msec. Some models (e.g., Wolfe et al., 1989) explicitly assume that each item takes a fixed amount of time to process (40 msec in Wolfe et al., 1989). That cannot be strictly true. It is easy to devise stimuli that will take an appreciable amount of time to classify once attention has been deployed to their location. Conjunctions of two colors (Wolfe et al., 1990) and judgments of spatial relations (Logan, 1994) may be two examples where the dwell time at each item is significantly longer than 40–50 msec.

What if the dwell time is significantly longer than 40–50 msec/item? Assertions about long dwell times can be used to argue for parallel models of search. For example, Duncan, Ward, and Shapiro (1994) assert that the dwell time is several hundred msec long (Ward, Duncan, & Shapiro, 1996).
If this were true, target–trial search rates of 25 or even 50 msec/item would reflect some parallel processing. This estimate of dwell time seems far too long. First, there is evidence that subjects can monitor a stream of sequentially presented items from a target letter or picture at rates exceeding eight items/sec (Chun & Potter, 1995; Lawrence, 1971; Potter, 1975, 1976). In addition, the experimental basis for the Duncan et al. claim, itself, is controversial (Moore, Egeth, Berglan, & Luck, 1996). Still, it would be an oversimplification to assume that each item in a visual search requires 50 msec to be categorized as a target or non-target.

4. Most Importantly, The Data Do Not Show a Serial/Parallel Dichotomy

The idea that searches can be divided into two classes, serial and parallel, is an attractive notion but it is simply not supported by the data (It was better supported when Treisman first proposed it back in 1980). Results of visual search experiments run from flat to steep RT × set size functions with no evidence of a dichotomous division. The evidence shows a continuum of search results. It is important to be clear about the implications of this fact. This does not mean that distinct serial and parallel mechanisms do not exist in visual search. The Guided Search model, for example, is built around the idea that the continuum can be explained by an early parallel mechanism working in tandem with a later serial mechanism (details in Wolfe, 1994a; Wolfe et al., 1989; see also Hoffman, 1979; Kinchla, 1977). The continuum of search slopes does make it implausible to think that the search tasks, themselves, can be neatly classified as serial or parallel.

Continua of search slopes can be found in both feature and conjunction searches. In the usual version of the dichotomy between parallel and serial searches, feature searches are supposed to be parallel searches. However, if one decreases the difference between the target and the distractor attributes, feature search slopes will rise smoothly from flat “parallel” slopes to steeper “serial” slopes. Thus, a search for green among red distractors will yield slopes near zero whereas a search for green among a yellowish green will produce more classically “serial” slopes (Nagy & Sanchez, 1990). Importantly, the steep, “serial” slopes are obtained for stimuli that are still clearly discriminable—separated by much more than one “just noticeable difference” (JND—Nagy & Sanchez, 1990). Similar results can be obtained for orientation (Foster & Westland, 1996; Foster & Ward, 1991a, 1991b) and, no doubt, for any other basic feature. Feature searches can also become “serial” if the distractors are sufficiently heterogeneous. The metric of heterogeneity is not trivial to describe. For example, under some circumstances a target of one color can be found efficiently among distractors of many different colors (Duncan, 1989; Smallman & Boynton, 1990; Wolfe et al., 1990), whereas, if different colors are picked, two distractor colors can yield steep search slopes for a third, target color (Bauer, Jolicoeur, & Cowan, 1996; D’Zmura, 1991). Similar effects have been observed in orientation searches with heterogeneous distractors (Alkhateeb, Morris, & Roodock, 1990; Moraglia, 1989; Wolfe, Friedman-Hill, Stewart, & O’Connell, 1992).

In general, it is hard to argue with the Duncan and Humphreys (1989) account, which holds that search becomes harder as target–distractor similarity increases and easier as distractor–distractor similarity increases. The hard work is in the details of what “similarity” means in this context.

Turning to conjunction searches, the steep “serial” slopes of Treisman and Gelade (1980) also turn out to be at the high end of a continuum of search slopes. In the past 10 years, a range of shallower slopes has been obtained from many different types of conjunction search (Cohen, 1993; Cohen & Ivry, 1991; Dehaene, 1989; Eguth, Virzi, & Garbart, 1984; McLeod, Driver, & Crisp, 1988; McLeod, Driver, Dienes, & Crisp, 1991; Nakayama & Silverman, 1986; Sagt, 1988; Theeuwes & Kooi, 1994; Treisman & Sato, 1990; von der Heydt & Dursteler, 1993; Wolfe, 1992a; Zohary & Hochstein, 1989).

Beyond the Serial/Parallel Dichotomy: How Shall We Describe Search Performance?

If we accept that the result of RT studies of visual search do not fall into two distinct groups that can be labeled “parallel” and “serial”, should we despair and declare the entire enterprise a hopeless mess? That seems too extreme. There is a clear difference between searches where the target “pops out” of the display and searches where each additional distractor makes it appreciably harder to find the target. These searches can be described as efficient in the former case and inefficient in the latter (see Fig. 1.5). Efficiency is merely a descriptive term and does not carry with it the theoretical baggage of “parallel”, “serial”, and so forth. Thus, search for a line of one orientation among distractors of one sufficiently different orientation is efficient with target–distractor slopes near zero msec/item (even if the lines are defined by other little lines; Bravo & Blake, 1990). Search for a rotated “T” among rotated “L’s” is inefficient with target–distractor slopes near 20 msec/item (Eguth & Dagenbach, 1991; Kwak, Dagenbach, & Eguth, 1991). Search for some conjunctions of two features (e.g. shape and color) might be described as quite efficient with target–distractor slopes less than 10 msec/item (e.g. Theeuwes & Kooi, 1994) but not as efficient (in this study) as conjunctions of shape and contrast polarity (slopes near zero; Theeuwes & Kooi, 1994). Finally, some searches like conjunctions of two orientations are very inefficient with target–distractor slopes significantly greater than 25 msec/item (Bilsky & Wolfe, 1995). The use of this sort of terminology would allow the
proponents of different models to speak about the data in a common language. It does not imply, however, an abandonment of the idea that an orderly and understandable set of underlying parallel and serial mechanisms produce the continuum of search results.

SECTION II: PREATTENTIVE PROCESSING OF VISUAL STIMULI

What Defines a Basic Feature in Visual Search?

In the heyday of the dichotomy between parallel and serial searches, a basic feature was a property that could support “parallel” visual search; that is, one that produced RT x set size slopes near zero. That definition becomes inadequate in the face of conjunction searches (Theeuwes & Kooi, 1994) or even triple conjunction searches (Wolfe et al., 1989) with near-zero slopes. One could propose that these conjunctions have featural status but this seems unparsimonious. It is one thing to propose that there are parallel processors for a set of basic features like color, orientation, size, and so forth. It is less appealing to argue for parallel representations of all the pairwise (and, perhaps, three-way) combinations of that initial list. This rapidly leads to combinatorial trouble.

Other criteria have been proposed for defining features (see Treisman’s 1986 review). One of these is that basic features support preattentive texture segmentation. A region of green spots in a field of red spots will be immediately segmented from the background. Similar results would be obtained with moving spots among stationary spots, spots at one stereoscopic depth among spots at another, and so on. It has been suggested that texture segmentation, by itself, defines basic features. However, Wolfe (1992a) showed that there are cases where stimuli that produce “effortless” texture segmentation do not produce efficient search and vice versa (see also Snowden, 1996). This is illustrated in Fig. 1.6. In Fig. 1.6a, it is quite easy to find either a black vertical or a white horizontal target, but the region that is made up entirely of target items does not segregate from the background items. In Figure 1.6b, the vertical and horizontal region does segment from the oblique background. However, search for a vertical or horizontal target among oblique distractors is quite inefficient (Wolfe et al., 1992). Neither efficient search nor effortless texture segmentation is sufficient to identify a “basic feature”. However, if a stimulus supports both efficient search and effortless segmentation, then it is probably safe to include it in the ranks of basic features. There do not seem to be any obvious exceptions to this rule.

Basic Features in Visual Search

With that preamble, this section will survey the evidence that various stimulus attributes are or are not basic features in visual search. There is reasonable consensus about a small number of basic features and more debate over several other candidates.

Color

To begin with perhaps the most straightforward case, color differences support efficient visual search and effortless texture segmentation. A long history of basic and applied research points to color as one of the best ways to make a stimulus “pop out” from its surroundings (Bundesen & Pedersen, 1983; Carter, 1982; D’Zmura, 1991; Farmer & Taylor, 1980; Green & Anderson, 1956; Moraglia, Maloney, Fekete, & Al-Bas, 1989; Smith, 1962;

FIG. 1.6. (a) Look for black vertical or white horizontal. (b) Look for vertical or horizontal.
Van Orden, 1993). With color, as with other basic features, we want to know what representation of the feature is used in search. Color is represented in a number of ways in the visual system. There is wavelength information at the retina. There are opponent-color representations in the relatively early stages of visual processing. At later stages of processing, there are the perceived colors of things in the world (Boynton, 1979; Lennie & D'Zmura, 1988). A few studies have looked in detail at the psychophysics of search for colored targets. Nagy and Sanchez (1990) compared JNDS for color stimuli with the color differences that would produce efficient search. The first important point to be taken from their work is that small differences between the color of targets and distractors will not support efficient search. As the difference shrinks, the slope of the RT \times \text{set size} function rises. Nagy and Sanchez (1990) identified the smallest color difference that supported efficient search. This can be thought of as a preattentive just noticeable difference (preattentive JND). For a given target color, it is possible to create an isopter representing this preattentive JND around the target color. Nagy and Sanchez compared this isopter to the MacAdam ellipse, the isopter defined by standard JNDS for color. These two types of JNDS are quite different. The preattentive JNDS are much larger and the isopter has a different shape. This means that there are clearly discriminable pairs of colors that do not support efficient visual search. The difference in isopter shape suggests that the preattentive JNDS are created by mechanisms different than those mediating simple color discrimination. Nagy, Sanchez, and Hughes (1990) examined these effects away from the fovea with comparable results.

Jolicoeur (personal communication) notes that Nagy and Sanchez's preattentive JNDS are collected under conditions quite different from those used to determine standard JNDS. When, for example, Jolicoeur and his colleagues repeated the Nagy and Sanchez experiments with stimuli that are isoluminant with the background, they found that smaller color differences would support efficient search. It seems likely that methodological concerns of this sort account for some, but not all, of the difference between preattentive and standard JNDS.

When there is more than one distractor color, efficient search is still possible but there are constraints. A number of experiments have shown efficient search for targets of unique color among at least nine distractor colors (Duncan, 1988; Smallman & Boynton, 1990 Wolfe et al., 1990). These searches with heterogeneous distractors are efficient only if the colors are widely separated in color space. When more similar colors are used, search is inefficient if the distractor colors flank the target color in color space (D'Zmura, 1991). D'Zmura has proposed that efficient search is possible whenever the target and distractor colors lie on different sides of a line drawn through color space. This is illustrated in Fig. 1.7, where Target T1 is

![Fig. 1.7](image_url)  
**Efficient search (linearly separable)**  
**Inefficient search (not linearly separable)**

FIG. 1.7. Linear separability in color space.

linearly separable from distractors D1a and D1b. This would correspond to something like a search for a white target among greenish (D1a) and yellowish (D1b) distractors. By contrast, T2 (bluish) would be hard to find among D2a (blue-green) and D2b (purplish) because the target is not linearly separable from the distractors. Search for T2 among D2a or D2b alone would be efficient. The same principle holds when more than two distractor colors are used. If the target falls inside the area of color space defined by the distractors, search is inefficient. If it falls outside, search is efficient. This linear separability account seems likely to hold only in a limited region of color space around any given target color. That is, linear separability holds if the color differences are not too large (see Bauer et al., 1996). No line in color space will explain the results of, say, Smallman and Boynton (1990) where nine different colors are used.

In her work on color search, Treisman speaks about search for prototypical colors. She argues that it is easier to find a deviation from a prototypical color than to find the prototypical color itself. This is her account for search asymmetries (Treisman & Gormican, 1988). The term "search asymmetry" describes a situation where it is easier to find A among B than to find B among A. For instance, in color search it is easier to find magenta among red distractors than red among magenta. Treisman's argument is that it is easier to find the deviation from red than to find red among deviants. Another way to describe the result is to say that targets are easy to find if and only if they contain some unique basic feature information. Magenta contains "blue" and can be found by looking for blue among distractors that are not blue. Red contains red, but so does magenta. This
search is less efficient because it is relatively more difficult to look for the "reddest" item or the "not blue" item. In this account, preattentive color space is divided into a few regions, a few basic colors. Indeed, many of the results with large color differences can be simulated in a model that assumes four basic colors in preattentive processing: red, yellow, green, and blue (Wolfe, 1994a). The apparently categorical description of large color differences and the linear separability account of search with smaller differences remain to be reconciled in a single description of the preattentive representation of color.

The preceding discussion of color ignores the role of black and white. Are they colors or do they represent a separate luminance feature? In some work, black and white behave like colors (Smallman & Boynton, 1990). Bauer, Jolicoeur, and Cowan (1996) find that a middle gray is hard to find when distractors are brighter and dimmer, following the linear separability principles described earlier. However, in other work, luminance seems to act more independently. Callaghan (1984) found that brightness variation had an effect on texture segmentation tasks that were based on hue, whereas hue did not have the same impact on tasks based on brightness. Theeuwes and Kooi (1994) report that conjunctions of contrast polarity and shape are easier to find than the easiest conjunctions of color and shape. Rensink and Enns (1995), and O’Connell and Treisman (1990) also propose preattentive properties of contrast polarity that are different than the properties of color. Moreover, attention seems to affect the perception of brightness (Tsai, Shalev, Zakay, & Lubow, 1994). The topic requires more systematic research. Specifically, the systematic work on color search has been done in two dimensions of color space. It needs to be extended into the third dimension, luminance.

Orientation

Orientation is another well accepted and well studied basic feature in visual search. Some of the properties of color as a feature are seen again when we turn to orientation. Preattentive JNDS can be plotted and they are larger than traditional JNDS (Foster & Ward, 1991a). Exact values will vary with variables like line length but a reasonable rule of thumb would be that subjects can discriminate between lines that differ by 1° or 2° in orientation but require a difference of about 15° to support efficient visual search with slopes near zero msec/item. Foster and his colleagues argue that performance on simple orientation tasks can be accounted for by two broadly tuned channels, one near vertical and one near horizontal (Foster & Ward, 1991b; Foster & Westland, 1995; Westland & Foster, 1996), although they find some second-order effects that would seem to require other preattentive orientation processes (Foster & Westland, 1992, 1995). Wolfe et al. (1992)

argue for channels roughly corresponding to the categorical terms "steep", "shallow", "left", and "right" (see also Mannan, Ruddock, & Wright, 1995).

This four-channel proposal is driven by data from experiments having more than one distractor orientation. If the distractors are of heterogeneous orientations, search becomes very inefficient (Moraglia, 1989a) unless one of two conditions is met. The target can be the item having the greatest local orientation contrast with neighboring distractors as shown in Fig. 1.8a. It is immediately clear that one of the two vertical lines in Fig. 1.8a is much more salient than the other because it is more dramatically different from its neighbors. In Fig. 1.8b, the same set of lines are rearranged and the vertical targets are harder to find (Jolicoeur, 1992; Moraglia, 1989a; Nothdurft, 1991b). The same effect of local contrast is seen in color (Nothdurft, 1991a, 1993b). Doherty and Foster (1995) cast some doubt on the importance of "local" in these "local contrasts". They show little change in performance as a function of stimulus density.

The other class of efficient orientation search is search for a target that is categorically unique. Wolfe et al. (1992) find that search is quite efficient even with heterogeneous distractors, if the target is the only "steep", "shallow", "left", or "right-tilted" item in the display. This is illustrated in Fig. 1.9 for "steep" targets.

In both panels of Fig. 1.9, the target is tilted 10° to the left of vertical and each distractor is either 40° or 60° different in orientation from the target. On the left, search is relatively efficient because the target is uniquely steep whereas on the right, search is less efficient because, while the target is the steepest item, it does not possess any unique categorical attribute (Wolfe et al., 1992).

The notion of four (or even of two) broadly tuned channels for the preattentive processing of orientation can go a long way toward explaining

![Fig. 1.8. Find the two vertical lines in each array.](image-url)
is not necessary to have an oriented edge in the luminance domain in order to have parallel processing of orientation. Illusory or subjective contours are a special case of second-order stimuli. They also appear to be available preattentively (Davis & Driver, 1994; Gurnsey et al., 1992).

In addition to the complexities of preattentive orientation processing already mentioned, one needs to consider the relationship between orientations. Symmetry between target and distractors makes it harder to find a 50° target among -50° distractors than to find the same target among -10° distractors, even though angular difference between target and distractors is greater in the former case than in the latter (Wolfe & Friedman-Hill, 1992a). Moreover, the angles formed by neighboring items in a display can be a clue to the presence of a target of unique orientation. That is, if there are two distractor types separated by 90° in orientation, a target of a third orientation can be found by the acute angle it will form with neighboring distractors. This works even if the orientations involved change from trial to trial (Wolfe & Friedman-Hill, 1992a). Meigen, Lagreze, and Bach (1994) report that the overall structure of the visual field modulates search performance. In their experiments, search for a tilted item was easier if the background, distractor items were colinear with each other.

The complexities of the preattentive processing of orientation are described in some detail here in part to make a larger point. It is widely held that the difficulty of a search task can be largely or even entirely explained by the similarity relationships between targets and distractors and between different types of distractors (Duncan & Humphreys, 1989). This is, no doubt, true, up to a point (Duncan & Humphreys, 1992; Treisman, 1991, 1992). However, any complete theory of visual search requires the working out of the details of preattentive similarity for each feature. They are likely to be reasonably complicated. Moreover, the rules for one feature may not generalize to another.

Curvature

Curvature is a reasonable candidate to be a basic feature. Treisman and Gormican (1988) found that curved lines could be found in parallel among straight distractors (see also Brown, Weisstein, & May, 1992; Gurnsey et al., 1992). Moreover, a search asymmetry exists. When the target is straight and the distractors are curved, search is less efficient. This suggests that curvature is a property whose presence is easier to detect than its absence. However, the alternative to curvature as a feature is that a curve might just be a point of high variation in orientation—a place where orientation is changing rapidly. Earlier assertions about the featural status of curvature (having nothing to do with visual attention) ran aground on this objection (Blakemore & Over, 1974; Riggs, 1973; Stromeyer & Riggs, 1974). Wolfe,
Yee, and Friedman-Hill (1992) tested this directly by having subjects search for curved targets among uncurved distractors that were roughly equated for local change in orientation. Efficient search for curvature remained possible (also see Cheal & Lyon, 1992; Fahle, 1991b). Only limited work has been done on the details of the preattentive processing of curvature. There is some evidence for categorical perception of curves (Foster, 1989).

**Vernier Offset**

Human observers are very good at detecting small departures from the colinearity of two line segments—a so-called vernier stimulus (Levi et al., 1985; Westheimer, 1979). In visual search, as shown in Fig. 1.10a, it is possible to detect the presence or absence of a vernier offset efficiently (Fahle, 1990, 1991a, 1991b; see also Steinman, 1987). Vernier offset might not be a feature in its own right. Like curvature, it could be a special case of orientation processing (Wilson, 1986). Fahle, however, has done a series of experiments that make this explanation unlikely (e.g. varying the overall orientation of the stimuli as in Fig. 1.10a). He also finds that while the presence or absence of a vernier break can be found efficiently, determining if a line is broken to the right or to the left requires attention (see Fig. 1.10b). Subjects could learn to do a left vernier among right-verniers search, but only on the basis of an orientation cue. The ability went away when Fahle disrupted the orientation cue inherent in a stimulus composed of vernier breaks in vertical lines. As with other features, the efficiency of vernier search increases with the difference between the target and the distractors (Fahle, 1990).

**Size, Spatial Frequency, and Scale**

There are at least three aspects of size that need to be considered in visual search experiments. (1) A target item can have different overall dimensions than other items, e.g. search for a large item among small items.

(2) A target item can have the same overall dimensions but can differ from other items in spatial frequency content; e.g. search for a patch of 3 cycle per degree grating among 6 cycle per degree distractors. (3) Finally, items can contain different information at different scales, e.g. Navon's stimuli in which one "global" letter was made up of a number of smaller "local" letters. Faced with an "S" made of smaller "I"'s, subjects could be asked to respond at either the global or the local scale (Kinchla & Wolfe, 1979; Navon, 1977).

Beginning with size, if the size difference is sufficient, a target of one size will be found efficiently among distractors of another size (Bilsky, Wolfe, & Friedman-Hill, 1994; Duncan & Humphreys, 1992; Müller, Heller, & Ziegler, 1995; Quinlan & Humphreys, 1987; Stuart, 1993; Treisman & Gelade, 1980). In conjunction searches (see below), size behaves like a feature orthogonal to other features such as orientation and color (Dehaene, 1989; Duncan & Humphreys, 1992; Dursteler & van der Heydt, 1992). A limited amount is known about the preattentive processing of size information. In Treisman's work on search asymmetries, she found that it was harder to find small among big than big among small (Treisman & Gormican, 1988). However, given one size of distractors, it was no easier to find a bigger target than a smaller one. Interpretation of this result is complicated by the fact that all slopes were steep. Like color and orientation, it is hard to find a target that is flanked by the distractors. Looking for the medium-sized item among larger and smaller items is inefficient unless the size differences are very large (Treisman & Gelade, 1980; Wolfe & Bose, unpublished data; see also Alkhatereb et al., 1990). Like orientation, search for stimuli of different sizes can be very efficient even if the contours of the stimuli are defined by chromatic change, texture, motion, illusory contours, etc. (Cavanagh et al., 1990).

Spatial frequency and size might be the same basic feature. Spatial frequency does behave like a basic feature in simple searches and in conjunction searches (Moraglia, 1989b; Sagi, 1988, 1990) but the experiments to explore the relationship between size and spatial frequency have not been done. As in size, a medium spatial frequency target is hard to find among lower and higher frequencies (Wolfe & Bose, unpublished data).

Scale is a property of stimuli that is related to size but is probably not identical to it. Intuitively, it seems that we can examine a scene at several scales. You can search a group of people for the biggest person, or for eyeglasses, or for the presence of gold cufflinks. The visual stimulus remains the same. The scale of the search changes. Navon (1977) argued that stimuli are processed first at a coarse, global scale and somewhat later at a finer local scale. Subsequent research has made it clear that the story is not quite that simple (Kinckla & Wolfe, 1979; LaGasse, 1993; Lamb & Robertson, 1990; Lamb & Yund, 1993; Robertson, Egly, Lamb, & Kerth, 1993). For instance,
Kinchla and Wolfe (1979) showed that observers would respond more quickly to the "local" letters if the global letter was very large. The original Navon proposal may hold for unattended stimuli (Paquet, 1992). See Kimchi (1992) for a review of this literature.

Verghese and Pelli (1994) show that subjects can select a scale at which to examine a visual search display. Farell and Pelli (1993) argue that, for some tasks, it is possible to monitor two scales at the same time. Moreover, it is possible to search for an item that is defined by a conjunction of two colors if those colors are in an hierarchical relationship to one another. That is, one can search efficiently for a red whole thing with a yellow part, but not for a red and yellow thing (Wolfe & Friedman-Hill, 1992b). This works as well for searches for the objects defined by the sizes of parts and wholes (Bilsky & Wolfe, 1995), but not for orientations of parts and whole (Bilsky & Wolfe, 1995; see discussion of conjunction search in Section III).

Motion

Motion is an uncontroversial basic feature. It is intuitively clear that it will be easy to find a moving stimulus among stationary distractors (Dick, Ullman, & Sagi, 1987; McLeod et al., 1988; Nakayama & Silverman, 1986). Not surprisingly, it is much harder to find a stationary target among moving distractors (Dick, 1989). Given stimuli that are moving, it is easier to find the fast target among slow distractors than vice versa (Ivry, 1992). Short-range apparent motion stimuli support efficient search but long-range stimuli do not (Dick et al., 1987; Horowitz & Treisman, 1994; Ivry & Cohen, 1990; although there is some question as to whether this long vs short distinction is the correct one to make—Cavanagh & Mather, 1989). The apparent motion results suggest that motion differs from orientation. While a vertical stimulus will pop out amongst horizontal distractors no matter how that stimulus is made (contours derived from color, motion, luminance etc.; Cavanagh et al., 1990), only certain motion stimuli work (short-range—yes: long-range—no). This distinction is bolstered by the finding that isoluminant motion stimuli are not available preattentively (Luschow & Nothdurft, 1993).

The broader point, worth reiterating, is that the rules for each feature need to be established for that feature and that generalization across features is risky. In the case of motion, the feature space includes axes of motion speed and direction. It is possible that these are separate features. More probably, they are aspects of a motion feature. Their interactions appear to be a bit complicated. For instance, heterogeneity in motion direction impairs search for an item of unique speed but heterogeneity in speed does not impair search for a unique direction (Driver, McLeod, & Dienes, 1992a). The behavior of motion stimuli in conjunction searches supports the notion that it is a basic feature (McLeod et al., 1988; Tiana, Lennie, & D'Zmura, 1989; Treisman & Sato, 1990) but a basic feature with its own, feature-specific rules (Driver, McLeod, & Dienes, 1992b; Duncan, 1995; McLeod, 1993).

Under natural conditions, retinal image motion may not reflect physical object motion. If the observer is moving (e.g. walking, driving) virtually all items in the field will move. Very little work has examined preattentive processing of the optic flow fields that result from observer motion. Bradick and Holliday (1991) found inefficient search for an expanding item among contracting items or vice versa. However, in these experiments, flow fields were local and oscillatory, not global as they would be with observer motion. Nothdurft (1993a, 1994) has done a series of experiments with gradients of motion. These are not intended to simulate observer motion but do show that the detectability of target motion depends on local distractor motion rather than on some combination of all motions present in the display. That is, a target moving upward is found efficiently if the local distractors are moving rightward even if distractors move upward in another portion of the field. In preliminary experiments with optic flow fields, observers can efficiently locate objects whose motion deviates significantly from those fields (Royden, Wolfe, Konstantinova, & Hildreth, 1996).

Shape

Probably the most problematical basic feature is shape or form. There are plenty of experiments that point toward shape features that are not reducible to orientation and curvature (e.g. Cohen & Ivry, 1991; Donderi & Zelhicker, 1969; Isenberg, Nissen, & Marchak, 1990; Quinlan & Jumphrey, 1987; Stefurak & Boynton, 1986; Theeuwes & Kooi, 1994; Tiana et al., 1989; Tsai & Lavie, 1988). However, the primitives of preattentive shape perception have been elusive. The heart of the problem is a lack of a widely agreed understanding of the layout of "shape space". Color space is a 2D plane or a 3D volume if you include luminance. One can argue about the precise axes but the general configuration is clear enough. Similarly, we know what we are talking about when we talk about orientation or size. It is much less obvious what the "axes" of shape space might be.

Several shape attributes have been suggested as candidate basic features. Perhaps the best supported is line termination (Julesz, 1984; Julesz & Bergen, 1983). In their paper on search asymmetries, Treisman and Gormican (1988) had subjects search for a "C" among "O"s or vice versa. Search was more efficient when the "C" was the target, suggesting that the gap or line terminators were the feature being detected. There are constraints on terminators as features. For example, whereas Julesz, using an "E" vs "S" task, had argued that a target with more terminators could be found amongst
distractors with fewer terminators, Taylor and Badcock (1988) reported that inefficient, apparently serial search was required for a target with seven terminators among distractors with only two. This would be consistent with the idea that only the simple presence of terminators is detected preattentively. Cheal and Lyon (1992) made matters more perplexing when they got a different asymmetry. Target-trial slopes for an “S” among “E”s (two vs three terminators) were somewhat shallower than slopes for an “E” among “S”s (three vs two terminators), although neither search was particularly efficient (14 msec/item for the former, 22 for the latter). Rotating the stimuli 90° to make “M”s and rotated “S”s made the searches a bit easier and maintained the asymmetry in favor of the target with fewer terminators. Enns (1986) found that the ability of terminators to support texture segmentation depends on the specific texture elements used. If elongated elements are used the presence or absence of terminators seems ineffective.

The opposite of line termination, in some sense, is closure. There is evidence that something like closure is important in the preattentive processing of form. Donnelly, Humphreys, and Riddoch (1991) have a series of experiments using stimuli like those shown in Fig. 1.11. In the more efficient case there, subjects seem to be detecting deviation from a “good figure”. A similar account may underlie Pomerantz and Pristach’s (1989) finding that adding the same element to targets and distractors can actually improve search. Examples of their stimuli are shown in Fig. 1.12.

Elder and Zucker (1993, 1994), using somewhat similar stimuli, argue explicitly for closure as a basic feature. Their experiments do show a clear effect of closure on search. Stimuli like those of Pomerantz and Pristach (1989) support more efficient search when the figures are closed by connecting the two lines to form a closed curve. However, Elder and Zucker’s closed-curve searches are not particularly efficient, so the evidence for the featural status of closure remains somewhat ambiguous (see also Enns, 1986; Williams & Julesz, 1989).

In a more general approach to the same issue, Chen (1982) has argued for a role for topological constraints in the parallel processing of form. For instance, he would consider a “hole” to be a preattentive feature. In an illusory contour experiment, he and his colleagues report that holes could appear to migrate from one item to another even if this requires the hole to change shape (Zhou, Zhang, & Chen, 1993). It is the “holeness” that seems to be preserved. Chen’s original work was criticized on methodological grounds (Rubin & Kanwisher, 1985) but subsequent work from this group tends to support a role for topology in the understanding of the preattentive analysis of form (Chen, 1990; Zhou, Chen, & Zhang, 1992).

Julesz has proposed that intersections are basic features or “texions” (Julesz, 1984, 1986; Julesz & Bergen, 1983). More recently, Bergen and Adelson have suggested that many of the demonstrations of pop-out of intersections could be explained by the operation of simple size-tuned filters with no need to invoke a mechanism sensitive to intersection (Bergen, 1991; Bergen & Adelson, 1988). Julesz and Kröse (1988) replied by filtering a texture of “+”s among “L”s to eliminate the size information. They report that texture segmentation survives this manipulation (they did not look at search tasks). However, one wonders if a simple non-linearity in early visual processing would restore the size cue to efficacy. The role of intersections as a feature in visual search tasks could benefit from further study.

Several candidate form primitives fail to support efficient visual search. “Juncture”, “convergence”, or “containment” (whether a dot was inside or outside a figure) were examined by Triesman and Gormican (1988). None of these produced particularly shallow RT × size functions. Biederman has proposed a set of primitives for solid shapes known as “geons” (Biederman, 1987). Although these may describe form perception for attended items, geons do not appear to be basic features (Brown et al., 1992).
Preattentive "Objects". There is a great deal more to the perception of form than holes, intersections, terminators, and so on. This is illustrated in Fig. 1.13. The same collection of local features can make a host of different objects or no object at all, if they simply gather together in one location. Is there any evidence that there is more to the preattentive processing of form than local features? Objects differ from collections of local features in at least two important ways. First, to state the obvious, they are objects. Once attention arrives, an object is not seen as collections of features. It is an object having certain featural attributes. Second, the spatial arrangement of the features is important—as for instance, in the layout of eyes, nose, and mouth in a face (Suzuki & Cavanagh, 1995).

In the original version of Feature Integration Theory, the purpose of attention was to bind features to objects (Triesman & Gelade, 1980) or, in a somewhat later formulation, to put the features in the correct "object files" (Kahneman & Treisman, 1984). More recent work shows that objects have some preattentive existence. Rensink and Enns (1995) have demonstrated that preattentive processes are sensitive to occlusion. Using stimuli like those in Fig. 1.14 in search experiments, they found that horizontal segments A and B were preattentively attributed to a single, occluded line as were C and D. Searching for "B" among A, C, & D is easy if all the segments are dissociated. B can be found because it is the longest. But if the segments are presented as shown in Fig. 1.14, "B" is hard to find because, in some sense, it does not exist.

We have conducted a series of conjunction experiments that make a similar point. In these experiments, items appear in front of and behind a lattice as schematized in Fig. 1.15. In each of the marked locations in Fig. 1.15, there are black, vertical contours. Visual search for a conjunction of color and orientation is not led astray by contours like those shown in "C" where the relevant color is owned by the object and the relevant orientation, by the lattice (Wolfe, 1996a). Results of this sort support the idea that objects are represented preattentively.

A second line of evidence supporting the preattentive status of objects comes from experiments that compare attentional deployment to objects vs attentional deployment to spatial locations. In Duncan's (1984) experiment, the stimuli were two overlapping objects. Subjects did worse when they had to make judgments about one property of each of two objects than when they made judgments about two properties of one object (see also Baylis, 1994; Baylis & Driver, 1993, 1995a, 1995b; Gibson, 1994; Vecera & Farah, 1994). If attention is directed to objects, it seems reasonable to assume that those objects had some preattentive existence in the visual system.

Yantis and his colleagues have performed a series of experiments in which abrupt onset stimuli attract attention in visual search tasks (see Yantis's chapter in this volume, and Jonides & Yantis, 1988a; Yantis & Egret, 1994; Yantis & Hillstrom, 1994; Yantis & Johnson, 1990; Yantis & Jones, 1991). Recently, Yantis has argued that these stimuli capture attention only if they indicate the creation of a new object—again suggesting that objects are available preattentively (Hillstrom & Yantis, 1994; Yantis, 1993; Yantis & Gibson, 1994; Yantis & Hillstrom, 1994; Yantis & Jonides, 1996).
Global Shape and the Position of Local Features. If two discriminable objects share all the same local features, it follows that the difference between them lies in the arrangement of those features. For instance, the only difference between 2 and S is the relative positions of the vertical lines. If the ability to process these relative positions in parallel exists, it is quite limited. Wang, Cavanagh, and Green (1994) found that subjects could search efficiently for a mirror-reversed “N” among “N’s” or a mirror-reversed “Z” among “Z’s.” These are searches for “novel” stimuli among well-known stimuli. The reverse searches are harder (N among mirror-N). The diagonal line in the Ns and the Zs changes orientation with mirror-reversal, providing a preattentive cue. However, the fact that this cue is only useful in the search for the mirror-reversed letters suggests some sort of sensitivity to the relationship of the diagonal lines to the vertical lines. The experiments of Heathcote and Mewhort (1993) also show that efficient search is possible on the basis of the spatial position of elements in an item. These results could reflect a preattentive sensitivity to phase information, a sensitivity that has been reported in texture segmentation experiments (Hofmann & Hallett, 1993).

Any information about spatial relationships must be fairly limited (see Tsai, Meiran, & Lamy, 1995). Searches for Ts among Ls are reliably inefficient when the Ts and Ls can be presented in several orientations (Kwak et al., 1991; Moore et al., 1996). Moreover, in a recent set of experiments, we have found no evidence for sensitivity to global shape (Wolfe & Bennett, 1996). In these experiments, subjects searched for targets among distractors that shared the same local features with the target but that differed markedly in global shape (e.g., search for a closed curve “chicken” among closed curve distractors made up of “chicken parts”). All of these searches were very inefficient (see also Biederman, Bickel, Teitelbaum, & Klatsky, 1988). The disparity between these results and results like those of Wang et al. (1994) suggest that the preattentive representation of form is still an open issue.

One final candidate for preattentive shape processing is face recognition. It seems clear that there are special-purpose mechanisms that process face information (Damasio, 1990; Farah, 1992; Kendrick & Baldwin, 1987; Purcell & Stewart, 1988; Rolls, Baylis, & Leonard, 1985; Rolls, Judge, & Sanghera, 1977; Thompson, 1980). However, visual search experiments indicate that this mechanism works on one face at a time. Searches for faces are inefficient (Kuehn, 1994; Nothdurft, 1993d; Reinitz, 1994; Suzuki & Cavanagh, 1995) although slopes are shallower than searches for non-face stimuli made of the same collection of lines and curves.

Pictorial Depth Cues

Curiously, while preattentive processing has, at best, a minimal representation of the shape of an object, there is quite good preattentive processing of depth. Depth is a cue that gives 3-D structure to those objects. Enns, Rensink, and their colleagues have done a series of ingenious experiments demonstrating that efficient search is possible on the basis of 3-D appearance of stimuli. Thus, subjects can find an apparently 3-D line drawing presented among flat items composed of similar lines in similar relationships (e.g., Tjunctions, Y-junctions; Enns & Rensink, 1991). They continue to do well with line drawings of targets that appear to differ only in 3-D orientation from the distractors (Enns & Rensink, 1990a, 1990b; see also Humphreys, Keulers, & Donnelly, 1994; and see Epstein & Balder, 1990; Epstein, Balder, & Bovnds, 1992, for more on the preattentive processing of slant information). Sun and Perona (1996a, 1996b) have similar evidence for preattentive processing of 3-D information but argue that the cue to efficient search is a difference in the apparent reflectance of targets and distractors—a difference that is the product of the 3-D calculations.

Efficient search can be based on shading cues to depth (Aks & Enns, 1992; Braun, 1993; Enns & Rensink, 1990a; Kleiner & Ramachandran, 1992; Ramachandran, 1988), occlusion cues (Rensink & Enns, 1995), slant from texture cues (Aks & Enns, 1993), and shadow cues (i.e., an implausible shadow pops out from among items with plausible shadows—Rensink & Cavanagh, 1993). Quite high-level cognitive factors seem to have an influence on processing of these depth cues (Brown, Enns, & Greene, 1993).

Stereoscopic Depth

Depth defined by stereoscopic cues also serves as a basic feature in visual search. Efficient search is possible when the target item lies at one depth and the distractors lie at another (Nakayama & Silverman, 1986a; see also Andersen, 1990; Andersen & Kramer, 1993). It is not necessary to have a difference in average depth between the targets and the distractors. Different directions of stereoscopic tilt will support efficient search (tilt into the page pops out from tilt out of the page—Hollliday & Braddick, 1991). Further, parallel processing of stereoscopic information can influence the perceived configuration of items in search tasks (He & Nakayama, 1992). There is some limited work on searches with multiple depth planes and asymmetries in O’Toole and Walker (1993) but the preattentive representation of stereoscopic space has not been worked out.

Is There Just a Single “Depth Feature”? It seems unlikely that there are separate parallel processes for each depth cue. More plausibly, visual search operates on a relatively “late” representation of the visual stimulus. Recall that Cavanagh et al. (1990) showed that many types of orientation stimuli would support efficient search. It didn’t matter if the orientation was defined by color, texture, motion, etc. The same may hold for a feature like depth. A fair amount of depth processing occurs in parallel. Nothing that
makes one item appear to stand out in front of all other items ought to support efficient search. If this is true, then we can predict that different depth cues would interfere with each other if pitted against each other in search tasks. We would also predict that other depth cues, like motion parallax, should support efficient search.

If some relatively high-level depiction of depth is the basic feature for search, it would not be surprising to find that other more sensory binocular cues do not support efficient search. Eye-of-origin information is readily available in the visual system (Bishop & Pettigrew, 1986; Blake & Cormack, 1979; Hubel & Weisel, 1962). However, a target presented to the left eye among distractors presented to the right is very difficult to find. Even a perceptually salient binocular phenomenon like binocular rivalry fails to support efficient search. Binocular rivalry occurs when different, unfusable stimuli are presented at corresponding loci in each eye (Blake, 1989; Breese, 1909; Helmholtz, 1924; Levelt, 1965). It is seen as an unstable alternation between the two monocular images. It can be perceptually quite salient and is an important aspect of binocular single vision, the ability to see one world with two eyes (Wolfe, 1986). Nevertheless, efficient search does not occur for one rivalrous target in a field of fused distractors nor for a fused target among rivalrous distractors (Wolfe & Franzel, 1988; but see Koch & Braun, 1996; Kolb & Braun, 1995).

Gloss

One variant of binocular rivalry does produce efficient search. If a spot is darker than the background in the image presented to one eye and brighter in the other eye, the resulting perception is one of lustre or gloss (Bulthoff & Blake, 1989; Helmholtz, 1924; Tyler, 1983). This glossy item can be found in parallel among matte distractors and a matte target can be found amongst glossy distractors (Wolfe & Franzel, 1988). Glossy surfaces give rise to highlights. Rensink and Cavanagh (1994) show preattentive sensitivity to the location of highlights.

Some Thoughts About the Set of Basic Features in Visual Search

Learning Features?

Depending on how you count them, there appear to be about eight to ten basic features: color, orientation, motion, size, curvature, depth, vernier offset, gloss, and, perhaps, intersection and spatial position/phase. There may be a few other local shape primitives to be discovered. A dozen or so hardwired primitives does not seem unreasonable. However, there is another alternative. Perhaps we learn the primitives we need. Evidence from visual search tasks that use letters and numbers as stimuli has been used to argue for the existence of learned features (Schneider & Eberts, 1980; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). Much of the early work on visual search was done with alphanumeric characters (e.g. Duncan, 1980; Eriksen & Eriksen, 1974) but this, by itself, doesn’t tell us anything about the featural status of the characters because the letter searches were often feature searches in alphanumeric guise. Thus, the distinction between Xs and Os may have little to do with their status as letters and more to do with the status of “curvature”, “intersection”, or “terminators” as basic features. On the other hand, it has been claimed that the numeral “0” is preattentively distinguishable from a set of letters and the physically identical letter “O” is preattentively distinguishable from a set of numbers (Egeth, Jonides, & Wall, 1972; Jonides & Gleitman, 1972). This is a claim about learned categories in preattentive processing but there have been problems with replication of the result (Duncan, 1983; Krueger, 1984; Francolini & Egeth, 1979; see Kelly, Harrison, & Hodge, 1991 for related material). The finding, described earlier, that some mirror-reversed letters can be found efficiently among homogeneous arrays of non-reversed letters makes a similar claim for the learning of new features (Wang et al., 1994; see also Wang & Cavanagh, 1993). It would seem that there is some evidence supporting the position that new features can be learned or, at the very least, that subjects can learn to better utilize the signal buried in the noise of a difficult search task.

What should one make of the evidence for learned features in visual search? One might expect that a new feature that was learned in one task would be useful in another. Treisman and Vieira failed to find such transfer (Treisman, Vieira, & Hayes, 1992; Vieira & Treisman, 1988); although Wang and Cavanagh (1993) found some transfer in tasks involving the learning of Chinese characters. As noted earlier, the “O” vs “zero” effect that seemed to point to parallel processing of semantic categories has been questioned. Claims for the pop-out of novel words (Hawley, Johnston, & Farnham, 1994; Johnston, Hawley, & Farnham, 1993; see also Soraci, 1992) have recently come under methodological attack (Christie & Klein, 1994). All of this might incline one toward skepticism about claims of learned features.

On the other hand, results like those of Wang and Cavanagh (1993; Wang et al., 1994) are very difficult to explain without invoking learning of something. The recent spate of papers on visual learning makes it clear that quite early stages of visual processing are subject to learning effects (e.g. Ahissar & Hochstein, 1993, 1995; Karni & Sagi, 1991, 1993; Karni et al., 1994; see Gilbert, 1994; Sagi & Tanne, 1994 for good, brief reviews). Moreover, there can be no doubt that visual search performance can improve with practice (Caerwinski, Lightfoot, & Shiffrin, 1992; Lee & Fisk, 1993; Rogers, 1992; Schneider & Eberts, 1980; Sireteanu & Retenbach, 1995). What remains in doubt is the nature of what is learned.
There is More Than One Set of Basic Features

The search for a set of visual primitives has a long history. A danger in the study of visual search is to assume that the set of primitives described for some other part of visual processing is or ought to be the set of primitives for search. Even when the same feature is found in two lists of basic features, caution should be exercised (see Shulman, 1990, for a related argument). Orientation is, perhaps, the best example because it has been so extensively studied. Cells sensitive to orientation first appear in primary visual cortex in primates. It is a convincing primitive of visual processing at that level (e.g. Hubel & Wiesel, 1974). Orientation is also a basic feature in visual search. However, the cortical orientation primitive and the preattentive orientation primitive have different properties. Preattentive processes can detect orientation differences on the order of 15° (Foster & Ward, 1991a, 1991b). Psychophysical orientation discrimination is much finer than that (Ozak & Thomas, 1986; Thomas & Gille, 1979). As noted earlier, preattentive processing of orientation appears to be categorical (Wolfe et al., 1992) and subjects can search for a uniquely oriented object defined by any number of properties; color, motion, texture (Cavanagh et al., 1990) or even other oriented elements (Bravo & Blake, 1990). All of this suggests preattentive orientation processing is several steps removed from the initial extraction of orientation information by primary visual cortex.

We don’t know if the same can be said about all other features. As noted earlier, it is dangerous to assume that rules for one feature apply to another. For instance, although Nagy and Sanchez (1990) found coarse processing of color information similar to that seen by Foster and Ward (1991a) in orientation, more recent work by Bauer et al. (1995) suggests that preattentive color vision need not be coarse and may be well described by simple operations in a fairly low-level (non-categorical) color space. Evidence from a texture task supports the idea that color and orientation may be processed differently (Nothdurft, 1993a; Wolfe, Chun, & Friedman-Hill, 1995). See Vergheese and Nakayama (1994) for different evidence that color and orientation are processed differently at a preattentive stage. For most other features, the relevant work has not been done.

The Preattentive World View

What does the preattentive world look like? We will never know directly, as it does not seem that we can inquire about our perception of a thing without attending to that thing. However, the experiments on visual search suggest that it is a world populated with objects or items that can be searched for and examined under attentional control but whose identity is not known preattentively. What is known about these objects is a listing of their surface properties. If the preattentive processing of orientation and size is any guide, the preattentive description of these surface properties is in a language similar to that used by a naive observer of an object. That is, it is big or small (not 3° of visual angle in extent). It is steeply tilted (not tilted 15° relative to vertical). Bauer et al. (1996) notwithstanding, it is probably “green” (not some wavelength or specific location in color space). (See Wolfe, 1993b, for a further discussion of this point.) To borrow terminology from Adelson and Bergen (1991), preattentive processes divide the scene into “things” and the preattentive basic features describe the “stuff” out of which perceptual “things” are made. The next section will discuss how subsequent processes use this information to find and/or identify these “things”.

SECTION III. USING PREATTENTIVE INFORMATION

Preattentive information exists to be used, not as an end in itself. In the previous section, we stressed the differences between preattentive processing of various features. Whatever those differences may be, preattentive processing of any feature can be used to guide the subsequent deployment of attention. In this section, we are specifically interested in the details of how preattentive information is used in visual search tasks. Ideas about the use of preattentive information are wrapped up in more general theories of visual search. The ideas put forth here will tend to be in the context of the Guided Search model (Version 2.0—Wolfe, 1994) but an effort will be made to acknowledge places where adherents of other models might differ in the interpretation of the data.

From the vantage point of Guided Search, preattentive processes exist to direct attention to the locations of interesting objects in the visual field. There are two ways in which a preattentive process can be used to direct attention: bottom-up (stimulus-driven) and top-down (user-driven). This distinction is not new. For example, Titchener (1919), speaking very generally about attention, distinguished between “primary attention” to something that was intrinsically interesting, and secondary attention—the volitional attention to something we should attend to. In the present context, we will distinguish between top-down and bottom-up forms of preattentive processing.

Bottom-up Processing

If a target is sufficiently different from the distractors, efficient search is possible even if the subject does not know the target’s identity in advance. Bravo and Nakayama (1992) showed this for the simple case where targets that could be red or green and distractors were whatever color targets were not. Found and Müller (1995; Müller, Heller, & Ziegler, 1995) obtained
similar results with stimuli that could be distinct in color, orientation, and size (although they did find a difference between the case where targets varied within a feature vs the case where targets varied across feature types, discussed later). This summoning of attention to an unusual item is what is usually meant when the term “pop-out” is used. Bottom-up pop-out appears to be based on a local difference operator (Julesz, 1986; Nothdurft, 1991b, 1993a, 1993b). If items are grouped by feature (e.g. color), attention will be attracted to the border where the feature changes (Todd & Kramer, 1994). One consequence of this local comparator is that some features searches may actually get easier as set size increases. More items mean greater density of items and stronger local contrasts (Bravo & Nakayama, 1992; Maljkovic, 1994). There is a continuum of pop-out. The salience of a pop-out target can be measured using standard psychophysical matching methods, matching the target salience with the salience of a luminance stimulus (Nothdurft, 1993c).

Top-down Processing

As the Titchenerian dichotomy indicates, we need preattentive processes to alert us to the presence of stimuli in the world that might be worthy of our attention. We also need to be able to use preattentive processes to deploy our attention to stimuli that we have decided are worthy of attention. That is, we need top-down, user-driven control of our preattentive processes. In searches for a target defined by a single feature, the clearest evidence for top-down control comes from color search tasks with very heterogeneous distractors. Even when each distractor is of a different color, it is possible to search efficiently for a target of a specified color (Duncan, 1989; Wolfe et al., 1990).

Top-down guidance of attention seems to involve a very limited “vocabulary”. As discussed earlier, orientation can only be specified as “steep”, “shallow”, “left”, “right”, and “tilted” (Wolfe et al., 1992). Sizes are “big” or “small” (Wolfe & Bose, unpublished data). Vernier offset is probably “broken” or “not broken” with the direction of the break not available (Fahle, 1990). The vocabularies for most other features have not been systematically studied but there is no reason to assume that they are significantly richer. Further restrictions are imposed on these few terms. In many searches, “top-down” specifications seem to be effectively limited to one term per feature—one color, one orientation, and so on. For instance, searches for targets defined by two colors or two orientations are very inefficient (Wolfe et al., 1990). In a color × color search, the target might be red and green while the distractors are a mix of red-blue and blue-green items. These searches would be efficient if observers could use top-down processing to select the items that were both red and green. However, it appears that top-down selection of red and green selects all items that are red and all items that are green—in this case, the set of all items.

As noted in the previous discussion of size and scale, two terms per feature per search can produce efficient search when one term applies to the whole object and the other term applies to a constituent part. Thus, it is possible to search efficiently for the red thing with a green part, perhaps because it is possible to select all red whole items and to select all green parts and to guide attention to the intersection (rather than the union) of those two sets (Wolfe, Friedman-Hill, & Bilsky, 1994). Interestingly, this part-whole processing works for color and size but not for orientation. Searches for a vertical thing with an oblique part are as inefficient as search for a vertical and oblique thing (Bilsky et al., 1994). Beyond limited information about object structure, there is some evidence for higher-order scene properties having an influence in top-down control of search (Brown, Enns, & Greene, 1993; He & Nakayama, 1992).

In Guided Search and related models, information from top-down and bottom-up analyses of the stimulus is used to create a ranking of items in order of their attentional priority. In a visual search, attention will be directed to the item with the highest priority. If that item is rejected, attention will move to the next item and the next so on (Wolfe, 1994). This is not the only way to understand the bottom-up, top-down distinction. For example, Braun and his colleagues have done a series of experiments where attention is tied up with a demanding task at fixation. They ask what attributes of a peripheral stimulus can still be evaluated in a brief presentation. Many of the basic features described in Section II survive this treatment (Braun, 1993, 1994; Braun & Julesz, 1996a, 1996b; Braun & Sagi, 1990a; see also Mack et al. 1992). Following William James, Braun argues that this is evidence for the concurrent activity of two types of attention—active (for the central task) and passive (for the peripheral task; Braun & Julesz, 1995). One could also argue that these results show that preattentive processing continues across the field while attention is busy elsewhere.

The division between top-down and bottom-up guidance of attention may be somewhat arbitrary. Maljkovic and Nakayama (1994, 1996) did a series of experiments in which observers had to report on the shape of a unique item in the field. For example, with color stimuli the unique item could be green among red items or red among greens. If the unique color remained constant, RTs were faster than if the color changed. This sounds like top-down, strategic control—“Select red”. However, it is not under the observer’s control. Predictable changes in the target color (e.g. alternating red-green-red-green over trials) produced RTs that were indistinguishable from unpredictable changes. If this is top-down control, the control comes from middle-management and not from the CEO.
Singletons, Attentional Capture, and Dimensional Weighting

The Maljkovic and Nakayama task is a variant of a singleton search. Singleton search is probably the simplest use of preattentive information in a visual search task. A single target is presented among homogeneous distractors and differs from those distractors by a single basic feature. Preattentive processing of the unique item causes attention to be deployed to that item so it is examined before any distractors are examined. As a result, RT is independent of the number of distractors presented. This account raises three questions:

1. Can irrelevant singletons attract attention?
2. Are there any irrelevant singletons that must attract attention?
3. If all singletons are relevant, are all singletons equivalent?

These are the topics of considerable ongoing research but, on the basis of present data, the answers appear to be: yes, no, and no. Detailed discussion of these matters (with potentially different answers) can be found in Yantis's chapter in this volume. The topic is important to an understanding of search and will be discussed briefly here. Beginning with Question 1, Yantis and his colleagues have done a series of experiments showing that the appearance of a new item can capture attention. In the basic onset paradigm, some items are created by the onset of stimuli while other items are created by deleting parts of existing stimuli. All else being equal, in a search through such items, attention will visit the onset stimuli first. (Jonides & Yantis, 1988b; Remington, Johnston, & Yantis, 1992; Yantis, 1993; Yantis & Johnson, 1990; Yantis & Jones, 1991). Early on, Miller (1989) raised methodological concerns about the paradigm, but these were controlled for in later experiments. Pashler (1988), using a different task, found evidence for disruption of search for a target in one featural dimension by the presence of a distractor in another. Abrupt onsets (or other indications of the creation of a new “object”) seem to be the most powerful singletons. Others, like color, capture attention in some cases (e.g. Theeuwes, 1992; Todd & Kramer, 1994) but not in others (e.g. Folk & Annett, 1994).

Turning to Question 2, it seems fair to say that there are paradigms where singletons must capture attention even if the subject does not want this to occur. However, it is not the case that there exist stimuli that capture attention across all paradigms. Here we are restricting ourselves to stimuli of the sort that would be presented in a visual search experiment—for who can doubt Sully when he says “One would like to know the fortunate (or unfortunate) man who could receive a box on the ear and not attend to it?” (Sully, The human mind, p. 146, quoted in Ladd, 1894). Theeuwes (1991, 1992, 1993, 1994, 1995) has a series of experiments showing, in particular, the attention-grabbing abilities of color and onset stimuli (see also Remington et al. 1992). Theeuwes would like to argue against a role for top-down processing but Bacon and Egseth (1994) argue that this mandatory capture occurs only if subjects are already looking for singletons. That is, onsets do not always capture attention but, if your task requires that you look for odd events, certain irrelevant odd events (e.g. onsets) will always interfere. If your task does not involve hunting for singletons, onsets may not disturb you. For example, Wolfe (1996a) presented abrupt onset spots every 40 msec during an inefficient search for Ts among Ls and found only a small, approx. 50 msec, additive cost compared to a no-spot condition. Mandatory attentional capture by each abrupt onset would have made the search task impossible.

Turning to Question 3, if singletons capture attention when the targets are, themselves, singletons, does the nature of the singleton matter? As was noted earlier, abrupt onsets seem to capture attention more vigorously than other singletons. Beyond that, there is evidence of top-down modulation of sensitivity to singletons. Treisman (1988a) reported on experiments in which subjects searched for singletons. Different targets appeared on different trials. If all the singletons were within one featural dimension, such as orientation, RTs were shorter than if singletons were spread over several dimensions. That is, RTs were shorter for a sequence of vertical target, horizontal target, oblique target than for a sequence of red, vertical, big. Pashler (1988) also found that irrelevant singletons within a dimension caused substantial disruption. Müller et al. (1995) have done a series of experiments expanding on this finding. They replicate the basic result and argue that the cause is “dimensional weighting”. Following models like Feature Integration (Treisman, 1993; Treisman & Gelade, 1980) and Guided Search (Wolfe, 1994a; Wolfe et al., 1989), they hold that there are several parallel feature processors whose output feeds a general salience map. A salience (or “activation”) map is a representation of visual space in which the level of “activation” at a location reflects the likelihood that that location contains a target. This likelihood is based on preattentive, featural information. In Guided Search, attention is deployed from peak to peak in the activation map in a search for the target. Thus, search is efficient if the target generates the highest or one of the highest activation peaks, as it will in a singleton search. Müller and Found (1995) argue that the contribution of any specific feature to the salience map is controlled by a weight that can change from task to task and, indeed, from trial to trial. They find that the RT for trial “N” is contingent on the relationship between target identity on trials “N” and “N-1” (See also Maljkovic & Nakayama, 1994, discussed earlier, and Found & Müller, 1995). That is, you are faster to find a color singleton on trial N if you found a color singleton on trial N-1.
If “redness” or “greenness” is being more heavily weighted on a given trial, how is that accomplished? Is attention made to favor “red” or to favor locations (or objects) that are red? The distinction is subtle but efforts to tease these apart suggest that it is locations that are favored, not features per se (Cave & Pashler, 1995; Shih & Sperling, 1996).

Conjunctions

Most searches in the real world are not searches for stimuli defined by single basic features. They are searches for stimuli that are defined by conjunctions of two or more features. You don’t look for “red”. You look for an apple that is some conjunction of red, curved, shiny, and apple-sized. Figure 1.16 shows a standard conjunction search; in this case, for a black vertical line among black horizontal and white vertical lines.

Treisman and Gelade (1980), in the original Feature Integration Theory, argued that all conjunction searches were serial, self-terminating searches. Like many an attractively strong claim, this one soon came under attack. There were technical matters—Houck and Hoffman (1986) found that the McCollough effect does not require attention even though the McCollough effect is a contingent after-effect based on a conjunction of color and orientation. Pashler (1987) argued that the slope ratios of target to blank trials did not correspond to the 2:1 ratio expected for a serial self-terminating search. Ward and McClelland (1989) reported that the variance of the blank trial RTs was greater than would be predicted by a simple, serial self-terminating model of conjunction searches. However, the worst problem for the claim came from evidence that conjunction searches could be done too efficiently to be described as “serial” searches. Egeth et al. (1984) reported that subjects could restrict search to an appropriately colored subset of items (see also Friedman-Hill & Wolfe, 1995; Kaptein, Theeuwes, & Van der Heijden, 1994). Nakayama and Silverman (1986a) found efficient search for conjunctions involving stereoscopic depth. The same held true for conjunctions of various features with motion (Driver, 1992a, 1992b; Driver et al., 1992a; McLeod et al., 1988, 1991). It seemed possible that strictly serial search was a general rule beset by a variety of exceptions, until a number of studies failed to produce serial, self-terminating results, even with the sorts of conjunction stimuli used in the original Treisman and Gelade studies. (Alkaitis, Morland, Ruddock, & Savage, 1990; Dehaene, 1989; Moraglia, 1989b; Mordkoff, Yantis, & Egeth, 1990; Quinlan & Humphreys, 1987; Tiana et al., 1989; von der Heydt & Dursteler, 1993; Wolfe et al., 1989; Zohary & Hochstein, 1989).

An important difference between the older “serial” conjunction searches and the newer, more efficient results seems to be stimulus salience. The most efficient searches occur with large differences between stimulus attributes—green vs red, vertical vs horizontal (Treisman & Sato, 1990; Wolfe et al., 1989). That said, we have been able to get very efficient results in conjunction searches with stimuli whose salience seems comparable to that reported in, for example, Treisman and Gelade (1980). We do not fully understand why conjunctions searches have become more efficient in the last 20 years.

**Other Influences on Efficient Search for Conjunctions**

Other constraints on the efficiency of conjunction search include stimulus density. Cohen and Ivry (1991) report that conjunction search becomes less efficient if items are packed closely together (see also Berger & McLeod, 1996). While we find that efficient search remains possible with the densities used by Cohen and Ivry (O’Neill & Wolfe, 1994; Wolfe, unpublished), it seems reasonable to assume that closer packing would, at some point, make it harder to determine which features went with which objects.

There are search asymmetries in conjunction search as there are in feature searches. However, the pattern of conjunction search asymmetries may not be obviously related to the asymmetries for the relevant features (Cohen, 1993). The topic can get quite complicated, as can be seen in an exchange of papers about asymmetrical asymmetries in motion × orientation conjunctions (Berger & McLeod, 1996; Driver, 1992b; Müller & Found, 1996; Müller & Maxwell, 1994): This may prove, perhaps, the futility of “theories of visual search that try to establish general principles that hold irrespective of the stimulus features defining the target” (Berger & McLeod, 1996, p. 114).

Conjunction search may also become somewhat less efficient with age (e.g. Zacks & Zacks, 1993; but see Plude & Doussard-Roosevelt, 1989). Given these constraints, efficient search seems possible for any pairwise combination of basic features. Triple conjunctions (e.g. search for the big, red, vertical target) tend to be more efficient than standard conjunctions (Dehaene, 1989; Quinlan & Humphreys, 1987; Wolfe et al., 1989). Recall also that, unlike conjunctions between two or more features, searches for
conjunctions of two instances of one type of feature are generally very inefficient (Wolfe et al., 1990) unless the features are in a part–whole relationship to each other (Wolfe et al., 1994). Even then, the part–whole relationships do not lead to efficient search for orientation × orientation conjunctions (Bilsky & Wolfe, 1995).

How is Efficient Conjunction Search Possible?

If one accepts the argument that there is a limited set of relatively independent basic features, efficient conjunction search becomes a puzzle to be solved. The original argument of Feature Integration Theory was that conjunction search had to be “serial” because there was no preattentive process that could find conjunctions (Treisman & Gelade, 1980). At the heart of the Guided Search model is an argument about how attention can be guided to likely conjunctions by combining information from two preattentive processes even if Treisman is correct about the absence of explicit parallel conjunction processing. For example, in a search for a red vertical target, a preattentive color processor could highlight or “activate” all “red” objects and a preattentive orientation processor could highlight all “vertical (or steep)” objects (e.g. Rossi & Paradiso, 1995). If these two sources of information are combined into a salience or activation map as described earlier, objects having both red and vertical attributes will be doubly activated. If attention is directed to the locus of greatest activation, it will find red vertical items efficiently even though none of the preattentive processes involved could recognize an item as simultaneously red and vertical. (See Cave & Wolfe, 1990; Wolfe & Cave, 1989; Wolfe et al., 1989 for the original Guided Search model, and Wolfe, 1992b, 1993a; and especially 1994a for the revised Guided Search 2.0 version. See Hoffman, 1979 for an earlier model with a similar architecture. See also Swensson, 1980. See Koch & Ullman, 1985, for an earlier version of an activation or salience map.)

Revised Feature Integration Theory has a similar account for conjunction searches, although one that proposes inhibition of distractor attributes rather than activation of target attributes (Treisman, 1988b, 1993; Treisman & Sato, 1990; Treisman et al., 1992; see Friedman-Hill & Wolfe, 1992, 1995 for an argument in favor of activation rather than inhibition).

There are other accounts of these results and, more generally, of the processes of visual search. Duncan and Humphreys (1989) proposed that the feature processes were not independent of each other and that search efficiency could be understood in terms of distances in a multidimensional similarity space—distances between targets and distractors and between different types of distractors. In brief, larger differences between target and distractor tended to make search easier, while larger differences between different types of distractors tended to make search harder. Moreover, they argued for a limited-capacity parallel search mechanism, rather than the serial, item by item mechanism invoked by Treisman and by Wolfe (Duncan et al., 1994). In a subsequent exchange with Treisman, Duncan acknowledged that basic features might have a degree of independence (Duncan & Humphreys, 1992; Treisman, 1991, 1992). Part of the limited-capacity parallel argument relies on the claim that attention moves only once every few hundred msec rather than every 40 or 50 msec as required by Treisman and by Wolfe. However, as noted earlier, that estimate (from Duncan et al., 1994) seems hard to reconcile with the ability to attend to discrete events occurring much more rapidly (Chun & Potter, 1995; Lawrence, 1971; Potter, 1975, 1976). Duncan and Humphreys’s stress on target–distractor and distractor–distractor similarity has been influential in interpreting experimental results and in shaping other theories of search.

Nakayama (1990) has a somewhat different account in which the demands of the task determine the scale at which items can be processed. A feature search makes minimal demands and the whole field can be processed at once. More complex searches make greater demands and cause processing to be limited to progressively smaller and smaller regions at one time. The relationship between scale and task in a model of this sort could be described in terms of the amount of information that can be processed in a single attentional fixation. Verghese and Pelli (1992) estimate this to be about 50 bits of information in one series of experiments. See Lavie and Tsal (1994) for related discussion using non-search paradigms, and see Green (1991) for an interesting analysis of model architectures of this sort.

Grouping

Several theories of search rely on grouping mechanisms to make conjunction search more efficient. Treisman (1982) has shown that conjunction search became more efficient as distractors were grouped by type. That is, in a search for red verticals, if all of the red horizontal items formed a single group, a red vertical item would pop out of that group on the basis of its orientation information alone (see Egget al., 1984; and see Farmer & Taylor, 1980 for similar results with feature search and also Bundesen & Pedersen, 1983). Ross and Mingolla (1994) have shown similar effects for color × color conjunctions. These grouping effects may be less marked in the elderly (Gilmore, 1985; but see Humphrey & Kramer, 1994). Most grouping accounts suggest that search can be speeded by processing and rejecting distractors in groups rather than one at a time (Grossberg et al., 1994; Humphreys, Freeman, & Muller, 1992; Humphreys & Muller, 1993; Muller, Humphreys, & Donnelly, 1994; Pashler, 1987).

Grouping effects do seem to have a role to play in search—a role that is not presently acknowledged by models like Guided Search (Duncan, 1995).
Even with small numbers of items, the sameness of two items may cause them to be treated together rather than in the strictly item by item manner of Guided Search or the original Feature Integration Theory (Baylis & Driver, 1992; Mordkoff & Yantis, 1993; Mordkoff et al., 1990). On the other hand, one burden on grouping models is to explain just how the grouping is done. For instance, Grossberg et al. (1994) make the reasonable suggestion that groups are formed by networks that group items that share a property and are not separated by other items that do not share that property (e.g., \{red\} GREEN forms one red group while \{red\} GREEN \{red\} forms two red groups). However, Wolfe (1994b), using some naturalistic stimuli, showed that color \times orientation searches could still be performed quite efficiently despite various colors and orientations intervening between virtually all “items” in the search. Probably a truly satisfactory model of search will need low-level grouping in addition to top-down and bottom-up selection processes.

Parallel Models

Returning to an issue raised at the start of this chapter, recall that it can be difficult to tell serial and parallel processes apart (Townsend, 1990). It makes sense, therefore, that there exist models with parallel architectures that do work similar to that done by parallel-serial architecture of Feature Integration and Guided Search. TVA (Theory of Visual Attention and FIRM (Fixed-capacity Independent Race Model) are examples of models of this kind (Bundesen, 1990, 1996; Shibuya & Bundesen, 1993; see also Logan, 1996). See Kinchla (1974) for an earlier incarnation and see also Mordkoff and Yantis (1991). In a similar spirit are models that frame the visual search problem in signal detection terms (Geisler & Chou, 1995; Palmer, 1994, 1995; Swensson & Judy, 1981) although signal detection theory is a tool that is useful across search models.

Other Issues in the Development of Attention

Eccentricity Effects

Most visual search studies ignore the effects of eccentricity. Not surprisingly, there are such effects and, not surprisingly, the main effect is that targets are located more slowly as their distance from fixation increases (Bursill, 1958; Carrasco & Chang, 1995; Carrasco, Evert, Change, & Katz, 1995; Cole & Hughes, 1984; Efron, 1990; Engel, 1971; Geisler & Chou, 1995; Lee, Jung, & Chang, 1992; Previc & Blume, 1993; Remington & Williams, 1986; Saarinen, 1993; Sanders, 1970; Sanders & Brück, 1991). In the study of attention, this effect of eccentricity is interesting to the extent that it can be seen as something more than a reflection of the general decline of acuity and sensitivity in the periphery. Evidence includes the finding that the eccentricity effect is not eliminated if the size of the peripheral targets is increased (Cole & Hughes, 1984) and the effect is dissociable from standard measures of visual fields (Ball, Owsey, & Beard, 1990). Moreover, variables like age (Ball et al., 1990; Madden, 1992; Scialfa, Kline, & Lyman, 1987), mental load (Egten, 1977), and stress (Bursill, 1958) all have an impact on search performance that seems to be separate from their effects on measures like acuity. In one recent study, Bennett and Wolfe (1995) equated the difficulty of a visual and an auditory vigilance task and found that the visual task had an effect on eccentricity functions in a standard search paradigm whereas the auditory task did not.

Ball and her colleagues have studied an attentional visual field measure that they call “the Useful Field of View” (or “UFOV”; Sekuler & Ball, 1986). The UFOV is a measure of an attentional visual field. It is smaller in the old than in the young (Ball et al., 1990), shrinks in the presence of auditory load in older subjects (Graves et al., 1993), is not well correlated with visual fields in subjects with healthy fields (Ball, Owsey, & Beard, 1990), and correlates with automobile accidents in an elderly population (Ball et al. 1993). These UFOV studies use a task that is rather different from standard visual search tasks and it remains to be seen if these results generalize to those standard tasks.

Illusory Conjunctions

A basic tenet of Feature Integration Theory and of related models like Guided Search is that features are “bound” together by the action of attention. Even if “red” and “vertical” are at the same physical location, they are not known to be two attributes of a red vertical thing until attention arrives on the scene. It follows that errors might occur in which features are incorrectly bound together. These errors are known as “illusory conjunctions” (Treisman & Schmidt, 1982). They tend to make their appearance when stimuli are briefly presented and the visual and attentional systems are left to construct a perception of the stimuli from decaying data (although it is possible to get illusory conjunctions with continuously visible stimuli and rigorous fixation—Prinzmetal, Henderson, & Ivry, 1995). Thus, subjects may report seeing a red vertical thing in a display that contains red things and vertical things but no red vertical things. Treisman’s original assertion was that preattentive features were “free-floating” and that any feature could conjoin with any other. She has subsequently declared that this free-floating terminology “got her into more trouble than anything else she ever wrote.” (Treisman, personal communication). Since the original claim, there have been several papers showing varying degrees of spatial restriction on illusory conjunction formation (Cohen & Ivry, 1989; Egin, 1987; Prinzmetal
et al., 1995; Prinzmetal & Keysar, 1989; but see Tsai, Meiran, & Lavie, 1994, exp. 3). Ashby, Prinzmetal, Ivry, and Maddox (1996) present a theory of illusory conjunctions based on position uncertainty.

Part of the difficulty in interpreting the meaning of illusory conjunctions might be traced to the possibility that illusory conjunctions are not produced by a single mechanism but by two or maybe more. Specifically, there are illusory conjunctions of low-level preattentive features that may be explainable as the consequence of a loss of position information at the level of the feature integration that is important for normal conjunction searches (e.g. Cohen & Ivry, 1989). There are also illusory conjunctions that involve the meaning of stimuli, usually—but not always—words (Prinzmetal, 1991; Treisman & Souther, 1986; Virzi & Egeth, 1984). Goolkasian (1988) found illusory conjunctions in the perception of clock time. It seems entirely possible, given a degraded or decaying representation, that higher-level attributes like “meaning” might seem to migrate in the same way that preattentive features might migrate. Similar processes might be occurring at two or several levels in processing. For purposes of understanding visual search, the danger arises in assuming that there is a single mechanism of illusory conjunction and, on the basis of that assumption, being forced into risky assertions about the preattentive processing of words or other complex stimuli.

Blank Trials

One area that has received relatively little attention is the termination of visual search trials when no target is found. It is easy enough to imagine how a truly serial search is terminated. You stop searching when all items have been examined. Rules for termination of more efficient searches are less obvious. Chun and Wolfe (1996) have proposed a solution in the context of the Guided Search model. As noted earlier, Guided Search proposes that an activation map is created on the basis of preattentive processing of basic features. This map ranks orders items from the most likely to be a target to the least. Chun and Wolfe (1996) propose that search proceeds through that list until the target is found or until no items remain with activations that are above an “activation” threshold. The remaining items are deemed unlikely to be targets and are not visited by serial attention. This threshold is set adaptively. It is pressured to be more conservative in order to minimize errors and pressured to be more liberal in order to minimize RT. In addition to this threshold mechanism, Chun and Wolfe propose that some trials are terminated by guesses and that the probability of guessing increases as search time increases. This guessing mechanism could produce the few false alarms seen in the data. This model does well in accounting for the blank trial data from a range of search tasks. See Zenger and Fahle (1995) for a somewhat different account.

Inhibition of Return

The Chun and Wolfe model and, indeed, all the search models with a serial component, need to ask how attention “knows” where it has been. For instance, a serial exhaustive search on a blank trial implies that each item is examined once and only once. One could inhibit each item or location after it is visited and rejected by attention—so-called “inhibition of return” (Gibson & Egeth, 1994; Mackebe & Nakayama, 1988; Posner & Cohen, 1984; Tipper, Driver, & Weaver, 1991). Klein (1988) reported finding evidence for inhibition of return in a search paradigm. Wolfe and Pokorny (1990) failed to replicate the finding. Moreover, Pratt and Abrams (1995) cued two items and found inhibition of return only for the most recently cued one. However, if models like Guided Search have any validity, there must be some way to keep track of the loci and/or objects that have been examined and rejected in the course of a search.

CONCLUSION

PsychINFO, the online database for Psychological Abstracts, listed 761 papers when given “visual search” as a subject heading on 23 February 1996. For all that research, some very basic questions remain to be fully answered. An incomplete list might include:

1. Is there a fixed set of basic features and, if so, what is the full list? As this chapter’s large section on this topic indicated, a credible list can be offered but, particularly in the area of preattentive shape/form processing, much work remains to be done.
2. What is the role of learning in preattentive processing? Specifically, when a task becomes efficient, as some tasks do with practice, is the observer building a new parallel process or isolating an attention-guiding signal from one existing preattentive process in the midst of the noise from the other processes?
3. What is an “item” in visual search? Is it an object? If so, how complete is preattentive processing of objects?
4. Whatever an item might be, is attention always limited to the processing of one item at a time? Alternatively, is it ever limited to one item at a time or are the limited-capacity parallel models a better representation of reality?
5. What happens after attention departs? If we assume that attention does something to the visual representation of an object, what post-attentive visual representation remains when attention is deployed
elsewhere? Preliminary investigation suggests that the post-attentive visual representation is the same as the preattentive representation (Wolfe, 1996b).

5. Finally, will any of the models of visual search survive the confrontation with the real world? In the real world, distractors are very heterogeneous. Stimuli exist in many size scales in a single view. Items are probably defined by conjunctions of many features. You don’t get several hundred trials with the same targets and distractors. The list could go on but the point is made. A truly satisfying model of visual search will need to account for the range of data produced in the laboratory, but it will also need to account for the range of real-world visual behaviors that brought us into the laboratory in the first place.

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1. VISUAL SEARCH


