Perception in Visualization

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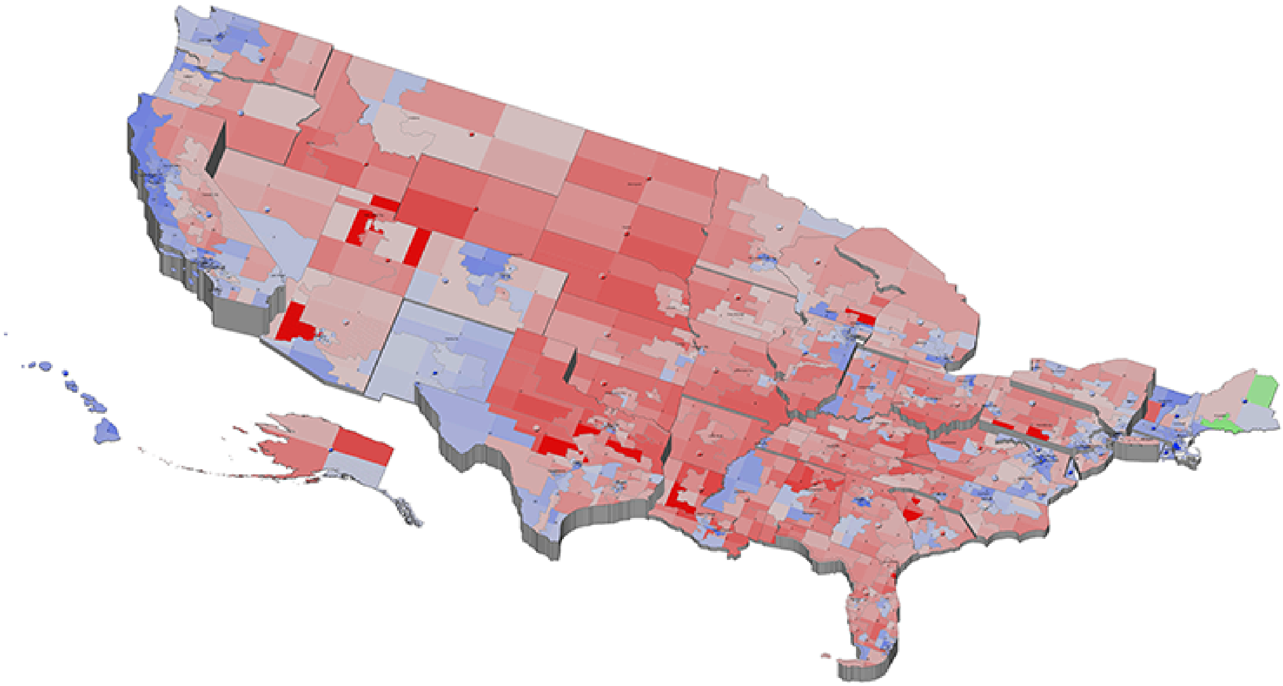


An example of a perceptually-motivated multidimensional visualization of recent U.S. election results (larger image or high-resolution PDF), each of the 435 congressional districts across the 50 United States are subdivided into four quadrants to show which party's candidate the district's voters selected for the 2004 Presidential election (upper-left quadrant), the most recent U.S. Senate election (upper-right), 2006 U.S. House election (lower-right), and the most recent Governor election (lower-left); color represents party (blue for Democrat, red for Republican, green for Independent), and saturation represents the winning percentage (more saturated for higher percentages); the small disc floating over each state shows aggregated state-wide results; incumbent losses are highlighted with textured X's; the height of a state represents the number of electoral college votes it controls

Note: An extended version of this web page has been accepted for publication in *IEEE Transactions on Visualization and Computer Graphics*. A reprint of this article is available on my publications page (abstract and PDF).

Introduction

Human perception plays an important role in the area of visualization. An understanding of perception can significantly improve both the quality and the quantity of information being displayed [Ware 2000]. The importance of perception was cited by the NSF panel on graphics and image processing that proposed the term "scientific visualization" [McCormick 87]. The need for perception was again emphasized during a recent DOE/NSF panel on directions for future research in visualization [Smith 98].

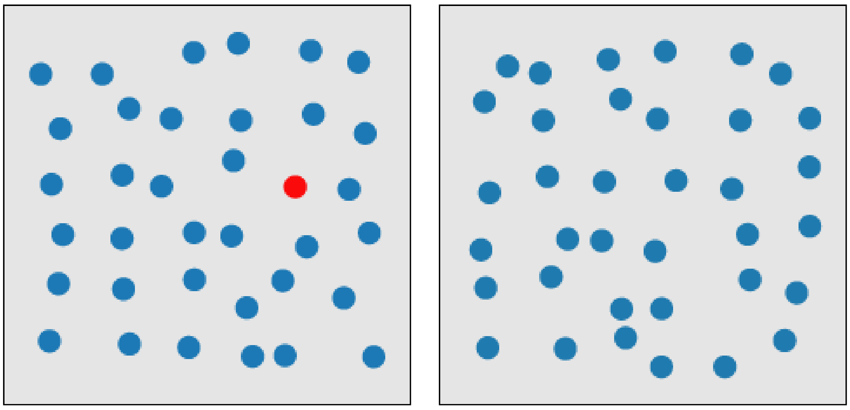
This document summarizes some of the existing theories in psychophysics, and discusses their relevance to scientific and information visualization. We begin with an overview of preattentive processing, the ability of the low-level human visual system to rapidly identify certain basic visual properties. We describe four theories of preattentive processing, and briefly discuss related work on postattentive vision and feature hierarchies. We next examine the new area of change blindness. Research on this phenomena offers a different perspective on early vision, suggesting that what we see can depend critically on where attention is focused. Finally, we describe a number of studies on the use of perception in visualization.

Preattentive Processing

For many years vision researchers have been investigating how the human visual system analyses images. An important initial result was the discovery of a limited set of visual properties that are detected very rapidly and accurately by the low-level visual system. These properties were initially called *preattentive,* since their detection seemed to precede focused attention. We now know that attention plays a critical role in what we see, even at this early stage of vision. The term preattentive continues to be used, however, since it conveys an intuitive notion of the speed and ease with which these properties are identified.

Typically, tasks that can be performed on large multi-element displays in less than 200 to 250 milliseconds (msec) are considered preattentive. Eye movements take at least 200 msec to initiate, and random locations of the elements in the display ensure that attention cannot be prefocused on any particular location, yet viewers report that these tasks can be completed with very little effort. This suggests that certain information in the display is processed in parallel by the low-level visual system.

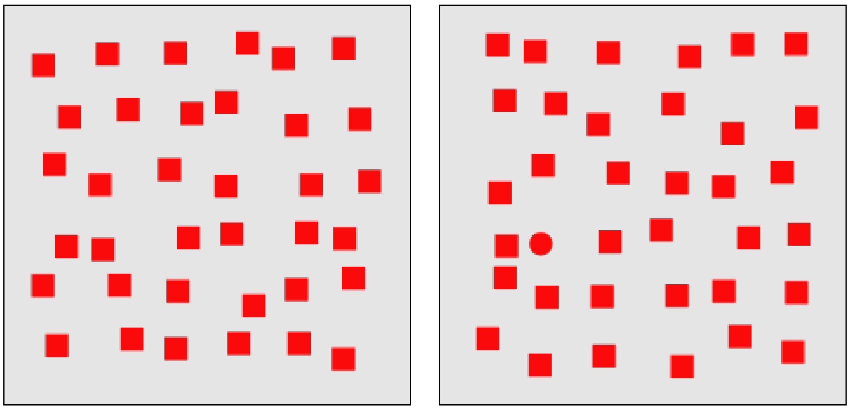
A simple example of a preattentive task is the detection of a red circle in a group of blue circles (Fig. 1). The target object has a visual property "red" that the blue distractor objects do not (all non-target objects are considered distractors). A viewer can tell at a glance whether the target is present or absent.



(a) (b)

Fig. 1: An example of searching for a target red circle based on a difference in hue: (a) target is present in a sea of blue circle distractors; (b) target is absent

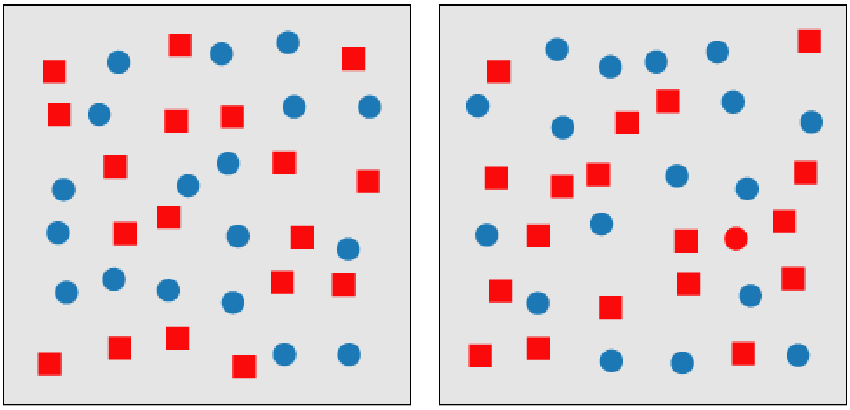
In Fig. 1 the visual system identifies the target through a difference in hue, specifically, a red target in a sea of blue distractors. Hue is not the only visual feature which is preattentive. In Fig. 2 the target is again a red circle, while the distractors are red squares. As before, a viewer can rapidly and accurately determine whether the target is present or absent. Here, the visual system identifies the target through a difference in curvature (or form).



(a) (b)

Fig. 2: An example of searching for a target red circle based on a difference in curvature: (a) target is absent in a sea of red square distractors; (b) target is present

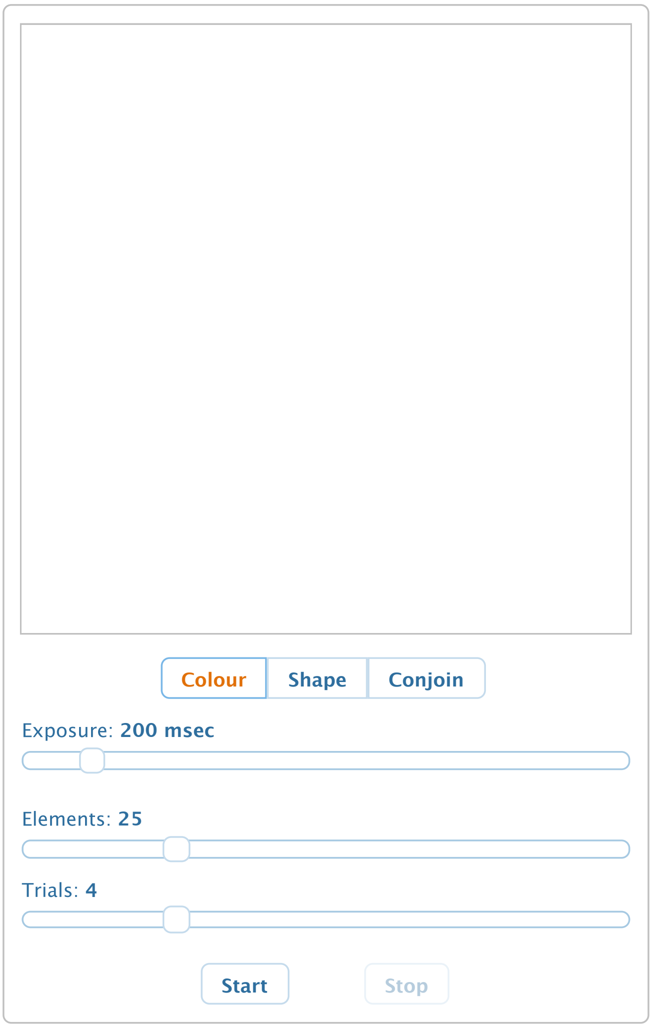
A unique visual property in the target (*e.g.,* a red hue in Fig. 1, or a curved form in Fig. 2) allows it to "pop out" of a display. A target made up of a combination of non-unique features (a *conjunction* target) normally cannot be detected preattentively. Fig. 3 shows an example of conjunction search. The red circle target is made up of two features: red and circular. One of these features is present in each of the distractor objects (red squares and blue circles). This means the visual system has no unique visual property to search for when trying to locate the target. If a viewer searches for red items, the visual system always returns true because there are red squares in each display. Similarly, a search for circular items always sees blue circles. Numerous studies have shown that this target cannot be detected preattentively. Viewers must perform a time-consuming serial search through the displays to confirm its presence or absence.



(a) (b)

Fig. 3: An example of a conjunction search for a target red circle: (a) target is absent in a sea of red square and blue circle distractors; (b) target is present

The Javascript applet below will let you experiment with the three different target detection searches: colour, shape, and conjunction. As in the figures above, the target is a red circle. Background elements are either blue circles (during colour searches), red squares (during shape searches), or blue circles and red squares (during conjunction searches). The "Exposure Duration:" slider lets you control how long each display is shown (anywhere from 100 to 1000 msec). The "Elements per Display:" slider lets you control the total number of elements in each display (from a minimum of 10 to a maximum of 70). The "Number of Trials:" slider lets you control how many displays to run.

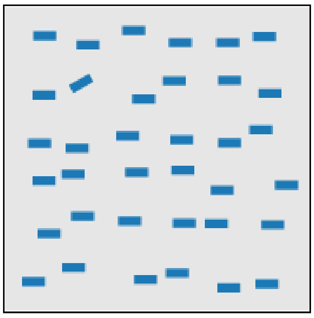


After each display, the applet will tell you whether the target was present or absent. This allows you to compare your answer with the correct answer for each display you see.

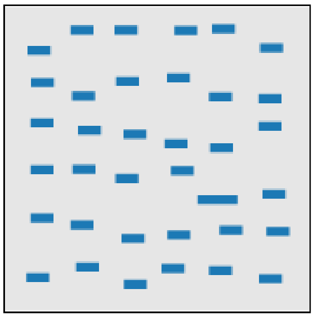
If the low-level visual system can be harnessed during visualization, it can be used to draw attention to areas of potential interest in a display. This cannot be accomplished in an ad-hoc fashion, however. The visual features assigned to different data attributes (the *data-feature mapping*) must take advantage of the strengths of our visual system, must be well-suited to the analysis needs of the viewer, and must not produce that visual interference effects (*e.g.*, conjunction search) that could mask information in a display.

Table 1 lists some of the visual features that have been identified as preattentive. Experiments in psychology have used these features to perform the following preattentive visual tasks:

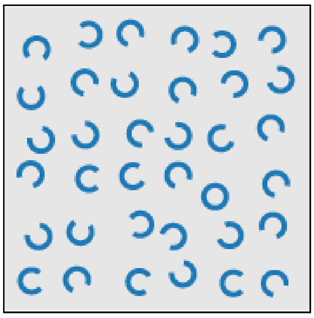
- *target detection:* users rapidly and accurately detect the presence or absence of a "target" element with a unique visual feature within a field of distractor elements (Figs. 1, 2, and 3),
- *boundary detection:* users rapidly and accurately detect a texture boundary between two groups of elements, where all of the elements in each group have a common visual property (Fig. 4),
- *region tracking:* users track one or more elements with a unique visual feature as they move in time and space, and
- *counting and estimation:* users count or estimate the number of elements with a unique visual feature.



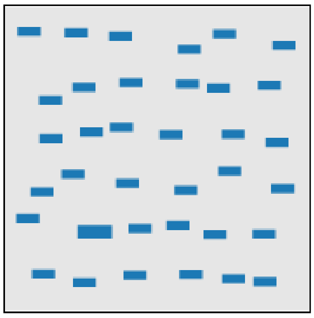
line (blob) orientation
Julész & Bergen 83; Sagi & Julész 85a, Wolfe et al. 92; Weigle et al. 2000



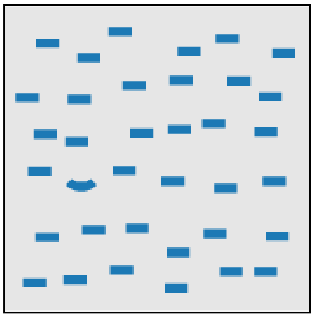
length, width
Sagi & Julész 85b; Treisman & Gormican 88



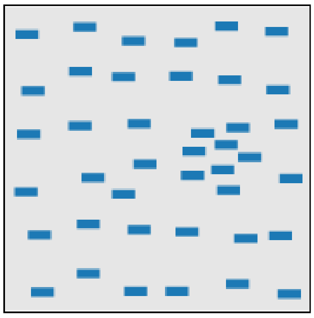
closure
Julész & Bergen 83



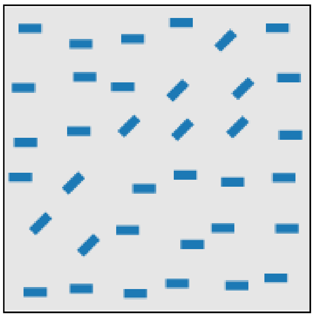
size
Treisman & Gelade 80; Healey & Enns 98; Healey & Enns 99



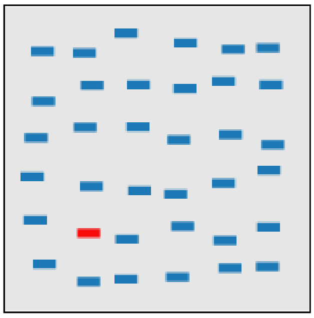
curvature
Treisman & Gormican 88



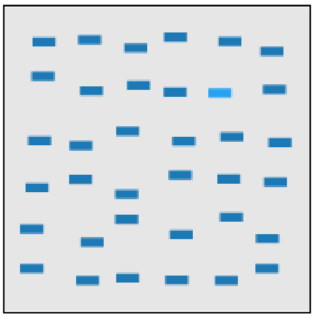
density, contrast
Healey & Enns 98; Healey & Enns 99



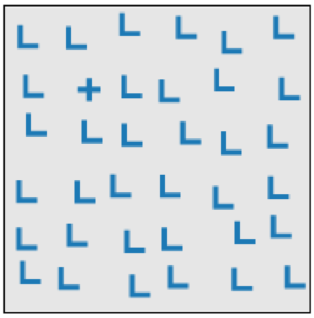
number, estimation
Sagi & Julész 85b; Healey et al. 93; Trick & Pylyshyn 94



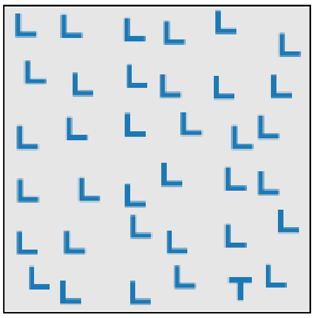
colour (hue)
Nagy & Sanchez 90; Nagy et al. 90; D'Zmura 91; Kawai et al. 95; Bauer et al. 96; Healey 96; Bauer et al. 98; Healey & Enns 99



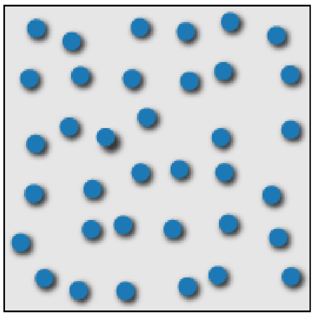
intensity, binocular lustre
Beck et al. 83; Treisman & Gormican 88; Wolfe & Franzel 88



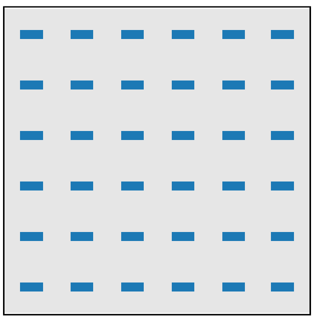
intersection
Julész & Bergen 83



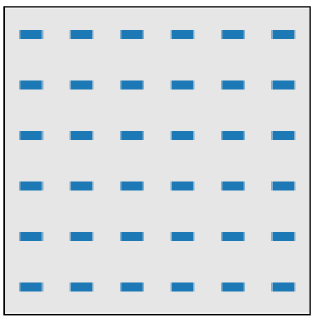
terminators
Julész & Bergen 83



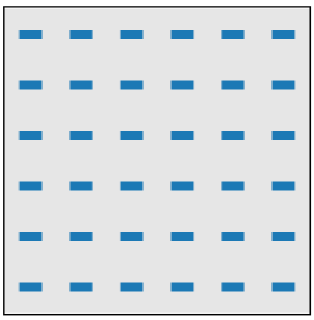
3D depth cues
Enns 90b; Nakayama & Silverman 86



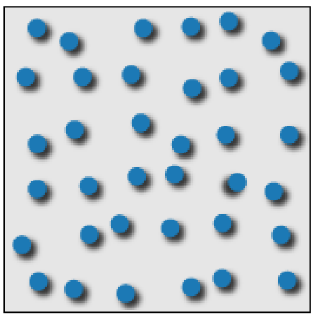
flicker
Gebb et a. 55; Mowbray &



direction of motion
Nakayama & Silverman 86;



velocity of motion
Tynan & Sekuler 82; Nakayama & Silverman 86; Driver &



lighting direction
Enns 90a

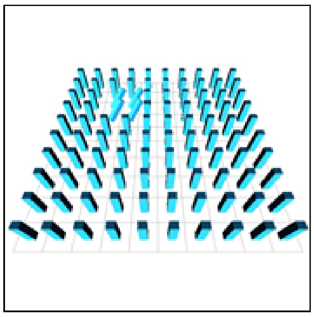
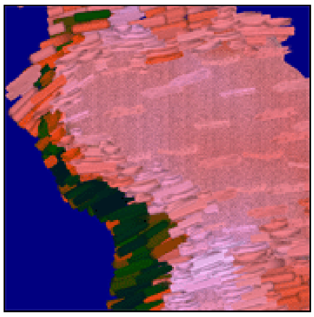
Gebhard 55; Brown 65; Julész 71; Huber & Healey 2005	Driver & McLeod 92; Huber & Healey 2005	McLeod 92; Hohnsbein & Mateeff 98; Huber & Healey 2005
		
	3D orientation Enns & Rensink 90a; Enns & Rensink 90b; Liu et al. 2003	**artistic properties** Healey 2001; Healey & Enns 2002; Healey et al. 2004

Table 1: A partial list of preattentive visual features, together with references to research that showed they were preattentive

Theories of Preattentive Processing

A number of theories have been proposed to explain how preattentive processing occurs within the visual system. We describe four well-known models: feature integration theory, texton theory, similarity theory, and guided search theory. We also discuss briefly the phenomena of postattentive vision, which shows that prior exposure to an scene does not help a viewer answer questions about the content of the scene.

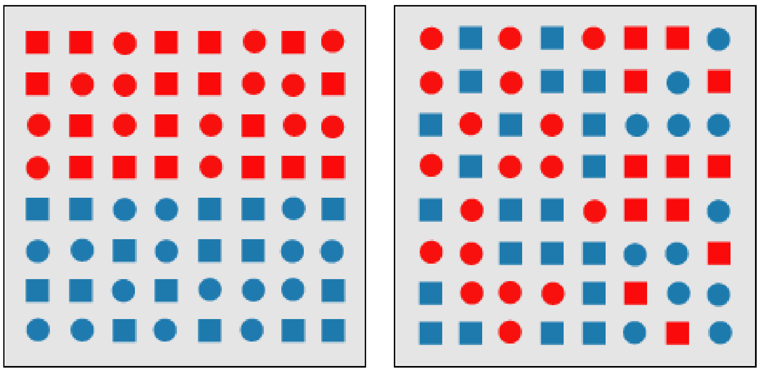
Feature Integration Theory

Anne Treisman was one of the original researchers to document the area of preattentive processing. She provided important insight into this phenomena by studying two important problems. First, she tried to determine which visual properties are detected preattentively [Treisman 91, Treisman & Gormican 88, Treisman & Souther 86]. She called these properties "preattentive features" [Treisman 85]. Second, she formulated a hypothesis about how the human visual system performs preattentive processing [Treisman & Gelade 80].

Treisman ran experiments using target and boundary detection to classify preattentive features. For target detection, subjects had to determine whether a target element was present or absent in a field of background distractor elements (Figs. 1 and 2). Boundary detection involved placing a group of target elements with a unique visual feature within a set of distractors to see if the boundary could be preattentively detected (Fig. 4).

Treisman and other researchers measured for preattentive task performance in two different ways: by response time, and by accuracy. In the response time model viewers are asked to complete the task (*e.g.*, target detection) as quickly as possible while still maintaining a high level of accuracy. The number of distractors in a scene is repeatedly increased. If task completion time is relatively constant and below some chosen threshold, independent of the number of distractors, the task is said to be preattentive. If the task were not preattentive, viewers would need to search serially through each display to confirm a target's presence or absence. Increasing the number of elements in the display would therefore produce a corresponding increase in the time required to report on the target.

In the accuracy model the display is shown for a small, fixed exposure duration, then removed from the screen. Again, the number of distractors in the scene varies (*i.e.*, increases) across trials. If viewers can complete the task accurately, regardless of the number of distractors, the feature used to define the target is assumed to be preattentive. A common exposure duration threshold is 200 to 250 msec, since this allows subjects only "one look" at the scene. The human visual system cannot decide to change where the eye is looking within this time frame.



(a) (b)

Fig. 4: An example of a boundary detection from Treisman's experiments: (a) a boundary defined by a unique feature hue (red circles and red squares on the top, blue circles and blue squares on the bottom) is preattentively classified as horizontal; (b) a boundary defined by a conjunction of features (red circles and blue squares on the left, blue circles and red squares on the right) cannot be preattentively classified as vertical

Treisman and others have used their experiments to compile a list of visual features that are detected preattentively (Table 1). It is important to note that some of these features are asymmetric. For example, a sloped line in a sea of vertical lines can be detected preattentively. However, a vertical line in a sea of sloped lines cannot be detected preattentively. Another important consideration is the effect of different types of background distractors on the target feature. These factors must often be addressed when trying to design display techniques that rely on preattentive processing.

In order to explain the phenomena of preattentive processing, Treisman proposed a model low-level human vision made up of a set of feature maps and a master map of locations. Each feature map registers activity in response to a specific visual feature. Treisman suggested a manageable number of feature maps, including one for each of the opponent colour primaries green, red, yellow, and blue, as well as separate maps for orientation, shape, texture, and other preattentive features.

When the human visual system first sees an image, all the features are encoded in parallel into their respective maps. A viewer can access a particular map to check for activity, and perhaps to determine the amount of activity. The individual feature maps give no information about location, spatial arrangement, or relationships to activity in other maps, however.

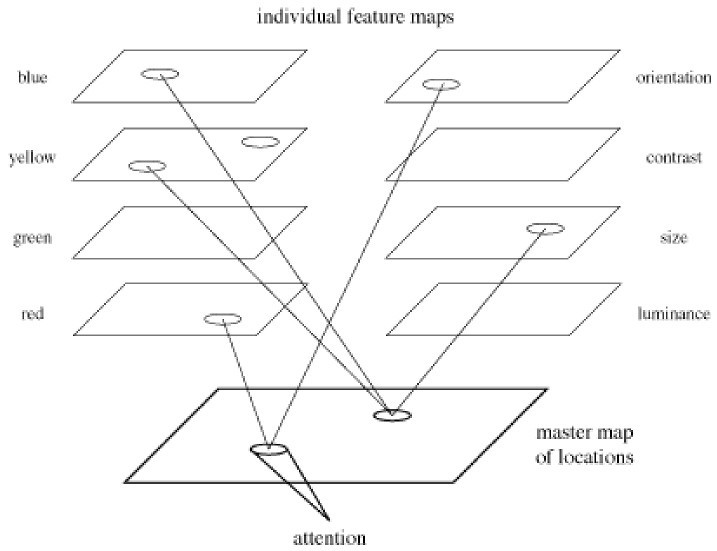


Fig. 5: Treisman's feature integration model for early vision; individual maps can be accessed to detect feature activity; focused attention acts through a serial scan of the master map of locations

This framework provides a general hypothesis that explains how preattentive processing occurs. If the target has a unique feature, one can simply access the given feature map to see if any activity is occurring. Feature maps are encoded in parallel, so feature detection is almost instantaneous. A conjunction target cannot be detected by accessing an individual feature map. Activity there may be caused by the target, or by distractors that share the given preattentive feature. In order to locate the target, one must search serially through the master map of locations, looking for an object with the correct combination of features. This use of focused attention requires a relatively large amount of time and effort.

In later work, Treisman has expanded her strict dichotomy of features being detected either in parallel or in serial [Treisman 91, Treisman & Gormican 88]. She now believes that parallel and serial represent two ends of a spectrum. "More" and "less" are also encoded on this spectrum, not just "present" and "absent". The amount of differentiation between the target and the distractors for a given feature will affect search time. For example, a long vertical line can be detected immediately among a group of short vertical lines. As the length of the target shrinks, the search time increases, because the target is harder to distinguish from its distractors. At some point, the target line becomes shorter than the distractors. If the length of the target continues to decrease, search time decreases, because the degree of similarity between the target and the distractors is now decreasing.

Treisman has also extended feature integration to explain certain cases where conjunction search is preattentive. In particular, conjunction search tasks involving motion, depth, colour, and orientation have been shown to be preattentive by Nakayama and Silverman [86], Driver et al. [92], and Wolfe et al. [89]. Treisman hypothesizes that a significant target–nontarget feature difference would allow individual feature maps to ignore nontarget information contained in the master map. For example, consider a search for a green horizontal bar within a set of red horizontal bars and green vertical bars. This should result in conjunction search, since horizontal and green occur within each of the distractors. In spite of this, Wolfe et al. [89] showed that search times are independent of display size. If colour constituted a significant feature difference, the red colour map could inhibit information about red horizontal bars. Thus, the search reduces to finding a green horizontal bar in a sea of green vertical bars, which can be done preattentively.

Texton Theory

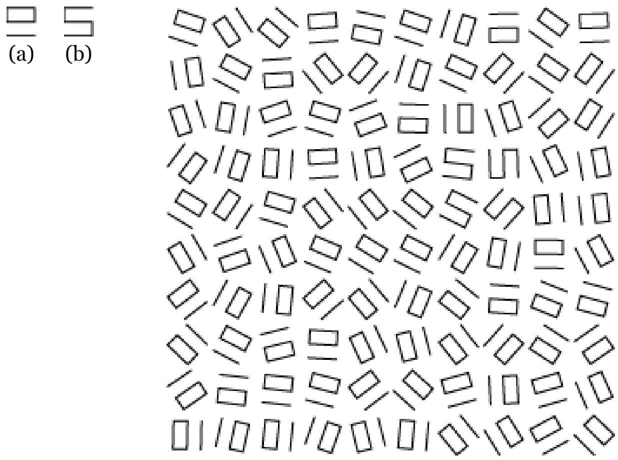
Bela Julész was also instrumental in expanding our understanding of what we "see" in an image. Julész's initial investigations focused on statistical analysis of texture patterns [Julész 71, Julész 75, Julész 81b, Julész et al. 73, Julész et al. 78]. His goal was to determine whether variations in a particular order statistic were seen (or not seen) by the low-level visual system. Examples of variations in order statistics include contrast (a variation in a texture's first-order statistic), orientation and regularity (a variation of the second-order statistic), and curvature (a variation of the third-order statistic). Unfortunately, Julész's results were inconclusive. First-order variations were detected preattentively. In addition, some (but not all) second-order variations were also preattentive, as were an even smaller set of third-order variations.

Based on these findings, Julész modified his theory of how preattentive processing occurs. He suggested that the early visual system detects a group of features called *textons* [Julész 81a, Julész 81b, Julész & Bergen 84]. Textons can be classified into three general categories:

1. Elongated blobs (*e.g.*, line segments, rectangles, ellipses) with specific properties such as hue, orientation, and width.

2. Terminators (ends of line segments).
3. Crossings of line segments.

Julész believed that only a difference in textons or in their density can be detected preattentively. No positional information about neighbouring textons is available without focused attention. Like Treisman, Julész suggested that preattentive processing occurs in parallel and focused attention occurs in serial.



(c)

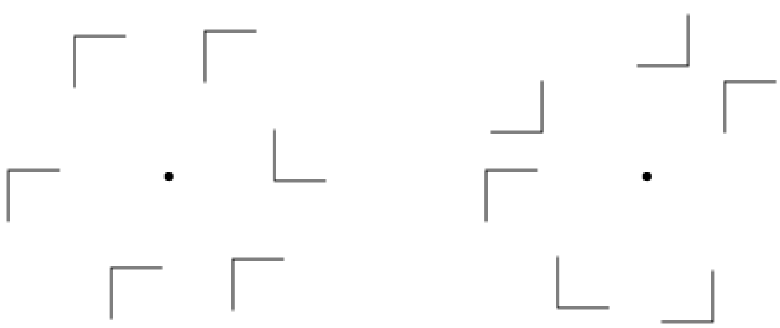
Fig. 6: An example of textons: (a,b) two textons (A and B) that appear different in isolation, but have the same size, number of terminators, and join points; (c) a target group of B-textons is difficult to detect in a background of A-textons when a random rotation is applied

Julész used texture segregation, the task of locating groups of similar objects and the boundaries that separate them, to demonstrate his theory (other researchers like Treisman also used this type of task, for example, identifying the orientation of the boundary between groups of common elements in Fig. 4). Fig. 6 shows an example of an image that supports the texton hypothesis. Although the two objects look very different in isolation, they are actually the same texton. Both are blobs with the same height and width. Both are made up of the same set of line segments and each has two terminators. When oriented randomly in an image, one cannot preattentively detect the texture boundary between the target group and the background distractors.

Similarity Theory

Some researchers do not support the dichotomy of serial and parallel search modes. Initial work in this area was done by Quinlan and Humphreys [87]. They investigated conjunction searches by focusing on two factors. First, search time may depend on the number of items of information required to identify the target. Second, search time may depend on how easily a target can be distinguished from its distractors, regardless of the presence of unique preattentive features. Treisman addressed this second factor in her later work [Treisman 88]. Quinlan and Humphreys found that Treisman's feature integration theory was unable to explain the results they obtained from their experiments. Duncan and Humphreys proceeded to develop their own explanation of preattentive processing. Their model assumes that search ability varies continuously, depending on both the type of task and the display conditions [Duncan 89a, Duncan 89b, Müller 90]. Search time is based on two criteria: T-N similarity and N-N similarity. T-N similarity is the amount of similarity between the targets and nontargets. N-N similarity is the amount of similarity within the nontargets themselves. These two factors affect search time as follows:

- as T-N similarity increases, search efficiency decreases and search time increases,
- as N-N similarity decreases, search efficiency decreases and search time increases, and
- T-N similarity and N-N similarity are related (Fig. 7); decreasing N-N similarity has little effect if T-N similarity is low; increasing T-N similarity has little effect if N-N similarity is high.



(a) (b)

Fig. 7: Example of N-N similarity affecting search efficiency for a target shaped like the letter L: (a) high N-N (nontarget-nontarget) similarity allows easy detection of target L; (b) low N-N similarity increases the difficulty of detecting the target L

Treisman's feature integration theory has difficulty explaining the results of Fig. 7. In both cases, the distractors seem to use exactly the same features as the target, namely oriented, connected lines of a fixed length. Yet experimental results show displays similar to Fig. 7a produce an average search time increase of 4.5 msec per additional distractor, while displays similar to Fig. 7b produce an average search time increase of 54.5 msec per additional distractor. In order to explain the above and other search phenomena, Duncan and Humphreys proposed a three-step theory of visual selection.

1. The visual field is segmented into structural units. Individual structural units share some common property (*e.g.*, spatial proximity, hue, shape, motion). Each structural unit may again be segmented into smaller units. This produces a hierarchical representation of the visual field. Within the hierarchy, each structural unit is described by a set of properties (*e.g.*, spatial location, hue, texture, size). This segmentation process occurs in parallel.
2. Because access to visual short-term memory is limited, Duncan and Humphreys assume that there exists a limited resource that is allocated among structural units. Because vision is being directed to search for particular information, a template of the information being sought is available. Each structural unit is compared to this template. The better the match, the more resources allocated to the given structural unit relative to other units with a poorer match.
3. Because units are grouped in a hierarchy, a poor match between the template and a structural unit allows efficient rejection of other units that are strongly grouped to the rejected unit.

Structural units with a relatively large number of resources have the highest probability of access to the visual short-term memory. Thus, structural units that most closely match the template of information being sought are presented to the visual short-term memory first. Search speed is a function of the speed of resource allocation and the amount of competition for access to the visual short-term memory

Given these three steps, we can see how T-N and N-N similarity affect search efficiency. Increased T-N similarity means more structural units match the template, so competition for visual short-term memory access increases. Decreased N-N similarity means we cannot efficiently reject large numbers of strongly grouped structural units, so resource allocation time and search time increases.

Guided Search Theory

More recently, Jeremy Wolfe has suggested a visual search theory that he calls "guided search" [Wolfe 94, Wolfe & Cave 89, Wolfe et al. 89]. He hypothesized that an activation map based on both bottom-up and top-down information is constructed during visual search. Attention is drawn to peaks in the activation map that represent areas in the image with the largest combination of bottom-up and top-down influence.

As with Treisman, Wolfe believes early vision divides an image into individual feature maps (Fig. 8). In his theory, there is one map for each feature type (*e.g.*, one map for colour, one map for orientation, and so on). Within each map a feature is filtered into multiple categories. For example, in the colour map there might be independent representations for red, green, blue, and yellow. Wolfe had already found evidence to suggest that orientation is categorized into steep, shallow, right, and left [Wolfe 92]. The relationship between values within a feature map is different than the relationship between values from different maps (*i.e.*, the relationship between "red" and "blue" is different than the relationship between "blue" and "shallow").

Bottom-up activation follows feature categorization. It measures how different an element is from its neighbours. Differences for each relevant feature map are computed and combined (*e.g.*, how different are the elements in terms of colour, how different are they in terms of orientation?) The "metrics" used to measure differences in each feature map are still being investigated.

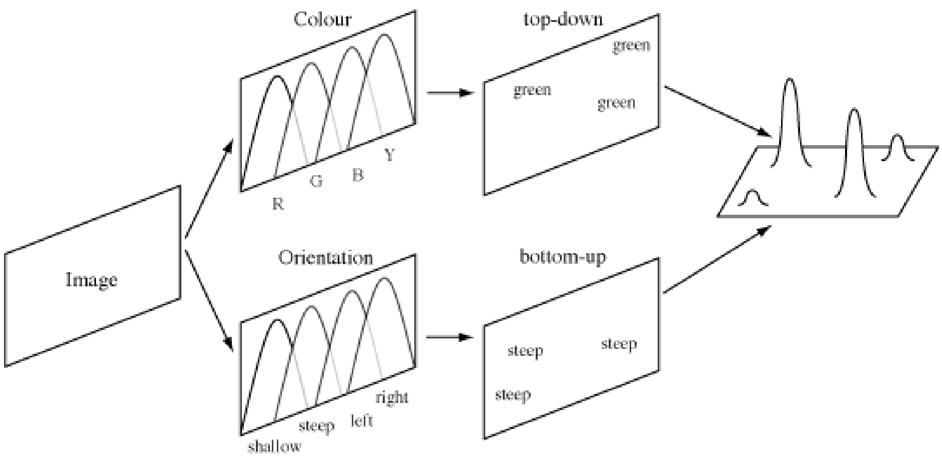


Fig. 8: Framework for guided search, user wants to find a green steep target; image is filtered into categories for each feature map, bottom-up and top-down activation "mark" regions of the image; an activation map is built by combining bottom-up and top-down information, attention is draw to the highest "hills" in the map

Top-down activation is a user-driven attempt to find items with a specific property or set of properties. For example, visual search for a blue element would generate a top-down request that activates "blue" locations. Previous work suggests subjects must specify requests in terms of the categories provided by each feature map [Wolfe & Franzel 88, Wolfe 92]. Thus, subjects could search for "steep" or "shallow" elements, but not for elements rotated by a specific angle. Obviously, subjects should pick the category that best differentiates the target from its distractors. Finding the "best" category is often nonintuitive, however. Wolfe suggests this might explain cases where subjects' performance for a task improves over time.

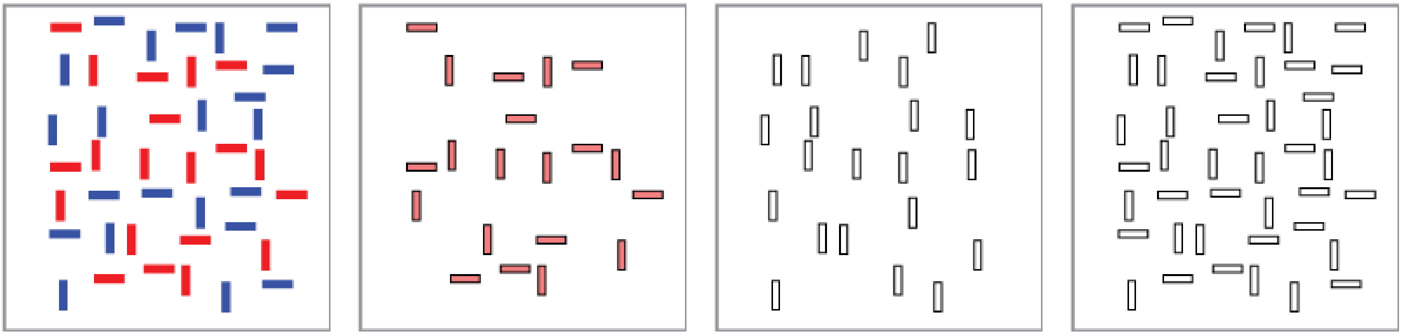
The activation map is a combination of bottom-up and top-down activation. The weights assigned to these two values are task dependent. A conjunction search would place priority on top-down information, since bottom-up results are, in essence, useless. Search for a target with a unique feature would assign a high weight to bottom-up activation. Hills in the activation map mark regions that generated a relatively large amount of bottom-up or top-down influence. There is no information in the activation map about the source of a hill. High activation from a colour map looks exactly the same as high activation from an orientation map. A subject's attention is drawn from hill to hill in order of decreasing activation.

Wolfe's theory easily explains traditional "parallel" visual search. Target elements produce the highest level of activation, regardless of the number of distractor elements. This causes the target to "pop-out" of the scene in time independent of the number of distractors. This also explains Duncan and Humphreys' similarity theory results. Low N-N similarity causes distractors to report higher bottom-up activation, since they now differ from their neighbours. High T-N similarity causes a reduction in the target elements' bottom-up activation. Moreover, guided search also provides a possible explanation for situations where conjunction search can be performed preattentively [Nakayama & Silverman 86, Wolfe 89, Wolfe 90]. User-driven top-down activation may permit efficient searching for conjunction targets.

Boolean Map Theory

A more recent model of low-level vision has been presented by Huang et al. [Huang and Pashler 2007, Huang et al. 2007]. This theory carefully divides a visual search task into two parts: *selection* and *access*. Selection involves choosing a set of objects from a scene. Access determines what properties of the selected objects a viewer can apprehend. Although both operations are implicitly present in previous theories, they are often described as a whole and not as separate steps.

Huang et al. propose that the visual system is capable of dividing a scene into exactly two parts: selected elements and excluded elements. This is the "boolean map" that underlies their theory. The visual system can then access certain properties of the selected elements in the map.



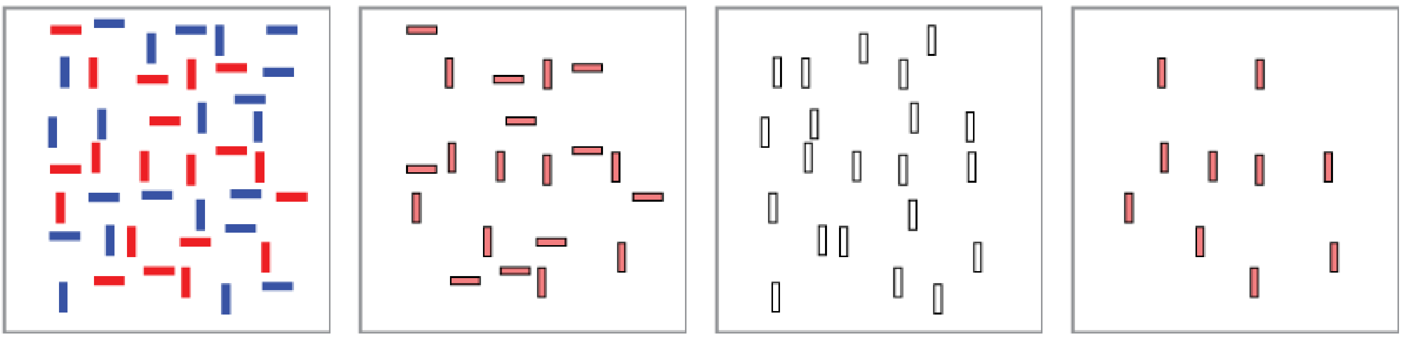
(a) (b) (c) (d)

Fig. 9: Boolean maps: (a) original scene with red and blue, vertical and horizontal elements; (b) boolean map on selection "red", colour label is red, orientation label is undefined; (c) boolean map on selection "vertical", orientation label is vertical, colour label is undefined; (d) boolean map on selection "all locations", colour label is undefined, orientation label is undefined

How are elements selected? That is, how is a boolean map created by the visual system? One way is for a viewer to specify a single value of an individual feature. All objects that contain the feature value are then selected. For example, a viewer could look for red objects, or vertical objects, or big objects. An important distinction between feature integration and boolean maps is that, in feature integration, presence or absence of a feature is available preattentively, but no information on location is provided. A boolean map, on the other hand, encodes the specific spatial locations of the elements that are selected.The boolean map contains feature labels to define properties of the selected objects. If, for example, a viewer selected red objects (Fig. 9b), the colour feature label for the resulting boolean map would be "red". Labels for other features (e.g. orientation, size) would be undefined, since they have not (yet) participated in the creation of the map.

A second method of selection is for a viewer to choose a set of elements at specific spatial locations. In this scenario, the boolean map would provide information about the spatial layout of the selected objects, but all feature labels would be undefined, since no specific feature value was used to identify the selected elements. Fig. 9 shows an example of a simple scene, and the resulting boolean maps for selecting red objects, selecting vertical objects, or selecting all locations.

Once a boolean map is available, what information can a viewer access? Two properties of a boolean map are available to a viewer: the label for any feature in the map, and the spatial location of the selected elements. For example, in Fig. 9b where red objects have been created, a viewer can access colour of any object as red, and can also identify the spatial locations of the selected objects. A viewer cannot, however, determine the orientation of a particular object in the map, because the orientation label is undefined. In order to locate, for example, vertical objects, a new boolean map based on this feature value must be created.



(a) (b) (c) (d)

Fig. 10: Set operations on boolean maps: (a) original scene with red and blue, vertical and horizontal elements; (b) boolean map on selection "red", colour label is "red", orientation label is undefined; (c) boolean map on selection "vertical", orientation label is "vertical", colour label is undefined; (d) boolean map from intersection of "red" and "vertical" maps, colour label is red, orientation label is vertical

A second way that a boolean map can be created is by applying set operators union and intersection on two existing maps (Fig. 10). For example, a viewer could create an initial map by specifying the colour feature value red (Fig. 10b). The viewer could then create a second map by specifying the orientation vertical (Fig. 10c), and intersect this map with the one currently held in memory. The result is a boolean map identify the locations of red, vertical objects (Fig. 10d). In this map, the colour label would be "red", and the orientation label would be "vertical". Note that a viewer can only hold and access one boolean map at any given time. The result of the set operation immediately replaces the viewer's current map. In this way, a viewer can search for composite objects (e.g. red, vertical objects) by applying a series of boolean map operations.

The boolean map model leads to some suprising and counterintuitive expectations, relative to existing preattentive models. For example, consider search for a conjunction target that is blue and horizontal in a sea of red horizontal and blue vertical objects. Theories like feature intergration and guided search dictate that this type of search is difficult, and the time required to find a target is proportional to the number of objects in the scene because search inspection is required. The boolean map theory says this type of combined feature search is more difficult that single feature search, because it requires two boolean map operations in series: creating a blue map, then creating a horizontal map and intersecting it against the current (blue) map to hunt for the target. Importantly, however, boolean map theory says that the time required for such a search is constant and independent of the number of objects in the display. The time to search for the target is simply the sum of the time required to complete the two boolean map operations.

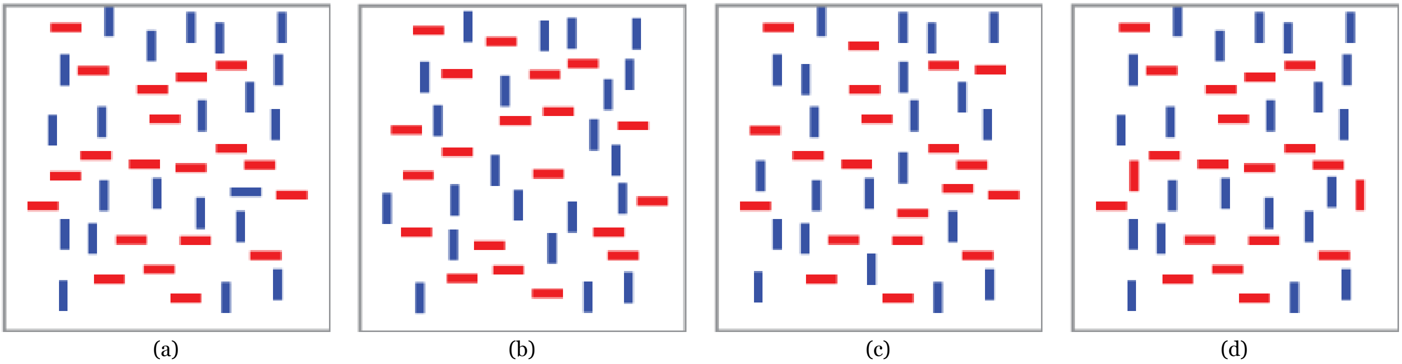


Fig. 11: Conjunction search using a boolean map strategy: (a-b) blue horizontal target, select "blue" objects first, then search within for a horizontal target, target present in (a), absent in (b); (c-d) a red vertical target, select "red" objects first, then search within for a vertical target, target absent in (c), present in (d)

Consider Fig. 11, which includes two conjunction targets, a blue horizontal object (Fig. 11a-b) and a red vertical object (Fig. 11c-d). Apply the following strategy to search for the target. In Fig. 11a-b, first search for blue objects, and once you have these "held" in your memory, look for the horizontal object within that group. For most observers it is not difficult to determine the target is present in Fig. 11a and absent in Fig. 11b when such a strategy is applied. A similiar search can be used to locate the red vertical target in Fig. 11c-d.

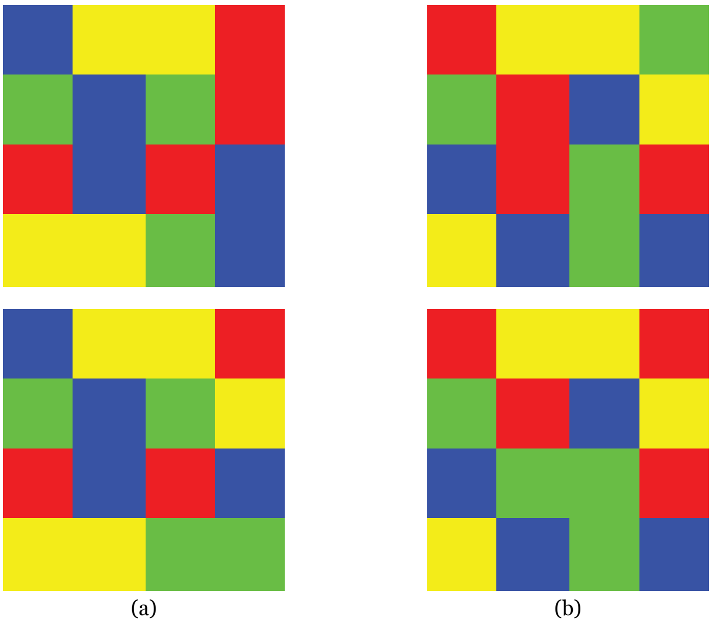


Fig. 12: Colour symmetry mismatch search: (a) two mismatches involving all four colours, one blue-green switch, one red-yellow switch; (b) two mismatches involving only two colours, two red-green switches

Another task that illustrates the boolean map theory is identifying differences in colour symmetry. Consider Fig. 12, where pairs of 16-element blocks are displayed with four colours: red, green, blue, and yellow. In each figure, there are two mismatched squares between the left and the right block. Fig. 12a's mismatches involve all four colours: one blue-green switch and one red-yellow switch. In Fig. 12b, however, the mismatches involve only two colours: two red-green switches. Boolean map theory says locating a mismatch in Fig. 12a will be, on average, faster than in Fig. 12b. This is because in Fig. 12a, no matter which colour value the viewer chooses to select on, a mismatch will always be present between the boolean maps. In Fig. 12b, only two colour values (red and green) will build maps that contain a mismatch. Viewer can confirm this for themselves. In Fig. 12a, focus on one of red, green, blue, or yellow. Notice that no matter which colour you choose, a mismatch will always be immediately visible between the two blocks. If you perform the same exercise on Fig. 12b, two boolean maps (red and green) contain a mismatch, but two boolean maps (blue and yellow) do not. It is therefore random whether the first maps selected in Fig. 12b contains mismatch, and therefore it should take, on average, 1.67 times longer to identify colour symmetry mismatches versus Fig. 12a.

Postattentive Vision

Preattentive processing asks in part: "What visual properties draw our eyes, and therefore our focus of attention to a particular object in a scene?" An equally interesting question is: "What happens to the visual representation of an object when we stop attending to it and look at something else?" Jeremy Wolfe addressed this question in his work on postattentive vision [Wolfe et al. 2000]. The intuitive belief that a rich visual representation accumulates as we look at more and more of a scene appears not to be true. This provides important insight into why the low-level visual system performs the way it does. The results also act as a bridge between preattentive processing and the new area of change blindness, which shows that people are often "blind" to significant variations that occur between glances at a scene.

Attention to different objects may allow a viewer to learn what is in a scene (if the objects are familiar and recognizable), but it does not allow the viewer to see the scene in a different manner. In other words, the preattentive visual representation of an object *after* a viewer studies it and looks at something else appears to be identical to its representation *before* the viewer studied it. No additional information is "saved" in the visual system after the focus of attention shifts to a new location.

Wolfe argues that if multiple objects are recognized simultaneously in the low-level visual system, it would involve a search for links between the objects and their representation in long-term memory (LTM). LTM can be queried nearly instantaneously, compared to the 40-50 msec per item required to search a visual scene or to access short-term memory. Preattentive processing can help to rapidly draw the focus of attention to a target with a unique visual feature (*i.e.*, little or no searching is required in the preattentive case). To remove this assistance, Wolfe designed targets with two critical properties (Fig. 13):

1. The targets were formed from a conjunction of features (*i.e.*, they could not be detected preattentively).
2. The targets were arbitrary combinations of colours and shapes (*i.e.*, they were not objects that could be semantically recognized and remembered on the basis of familiarity).

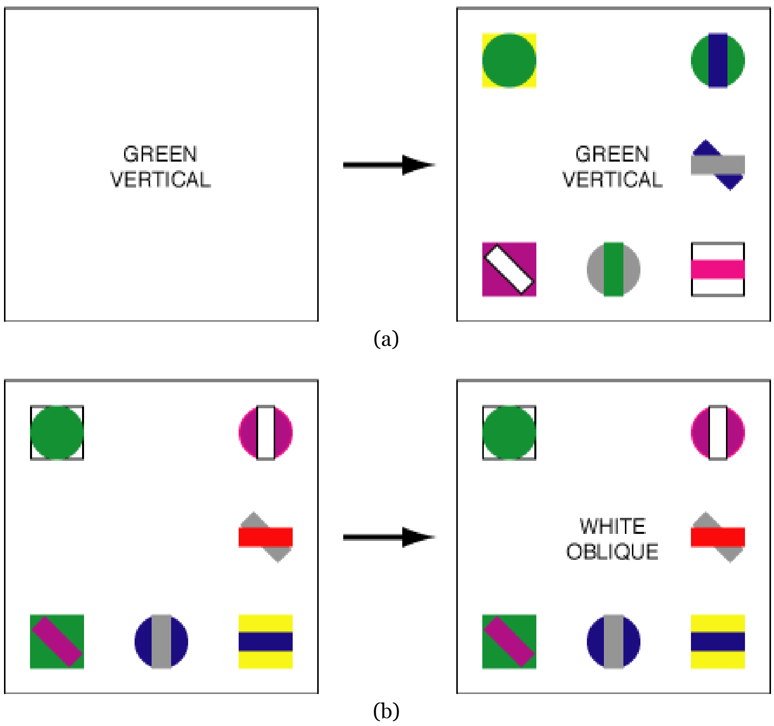


Fig. 13: Examples of search for color-and-shape conjunction targets, both with and without a preview of the scene: (a) no preview of the scene is shown (although text identifying the target is shown prior to the search), in this case the green vertical target is present; (b) a preview of the scene is shown, followed by text identifying the target, in this case a white oblique target is not present

Wolfe initially tested two search types. In both cases, viewers were asked to answer as quickly as possible while maintaining a high level of accuracy (*i.e.*, a response time search):

1. *Traditional search.* Text on a blank screen was shown to identify the target. This was followed by a display containing 4, 5, 6, 7, or 8 potential target objects in a 3-by-3 array (formed by combinations of seven colours and five shapes, Fig. 13a).
2. *Postattentive search.* The display to be searched was shown to the user for a specific duration (up to 300 milliseconds). Text identifying the target was then inserted into the scene (Fig. 13b).

Results showed that the postattentive search was as slow (or slower) than the traditional search, with approximately 25-40 msec per object required for the target present trials. This implies that previewing the scene provides no advantage to the viewer for finding a conjunction target. In order to explore further, Wolfe studied a number of different search scenarios to test for any benefit from previewing the scene:

- *Repeated search:* viewers were asked to search the same display five times for five different targets. The display was shown with target text, and after an answer was provided (target present or absent), the target text changed to identify a new target. This experiment tested whether additional exposure to the display improved search performance.
- *Repeated search with letters:* viewers searched in a manner identical to repeated search, but with displays containing letters rather than combinations of colours and shapes. This experiment tested whether the type of target used affected search performance.
- *Repeated search versus memory search:* viewers were asked to search a group of five letters 350 times for a target letter. Half the viewers were shown the five letters. The other half were required to memorize the five letters prior to the target queries. This experiment tested whether a prolonged exposure to a set of objects improved search performance. It also tested to see how visual search and short-term memory search performance differed.

In each case viewers continued to require 20-50 msec per object to complete the search. Wolfe's conclusion was that sustained attention to the objects tested in his experiments did not make visual search more efficient. This has a significant potential impact for visualization design. In most cases, visualization displays are novel, and their contents cannot be committed to long-term memory. This means that studying a display may offer no assistance in searching for specific data values. In this scenario, methods that draw attention to areas of potential interest within a display (*i.e.*, preattentive methods) would be critical in allowing viewers to rapidly and accurate explore their data.

Feature Hierarchy

Based on our understanding of low-level human vision, one promising strategy for multidimensional visualization is to assign different visual features to different data attributes (*i.e.*, building a *data-feature mapping* that maps data to a visual representation). This allows multiple data values to be shown simultaneously in a single image. One key requirement of this method is a data-feature mapping that does not produce visual interference. Interactions between different visual features hide or mask information in a display. Obviously, we want to avoid this situation during visualization. One simple example of visual interference is the conjunction search shown in Fig. 3. If we want to search rapidly for combinations of data values, care must be taken to ensure the resulting combinations contain at least one unique feature for the visual system to cue on.

Other types of visual interference can also occur. An important type of interference results from a *feature hierarchy* that appears to exist in the visual system. For certain tasks the visual system seems to favour one type of visual feature over another. For example, during boundary detection researchers have shown that the visual system favours colour over shape (Fig. 14). Background variations in colour interfere with a viewer's ability to identify the presence of individual shapes and the spatial patterns they form [Callaghan 90]. If colour is held constant across the display, these same shape patterns are immediately visible. The interference is asymmetric: random variations in shape have no effect on a viewer's ability to see colour patterns.

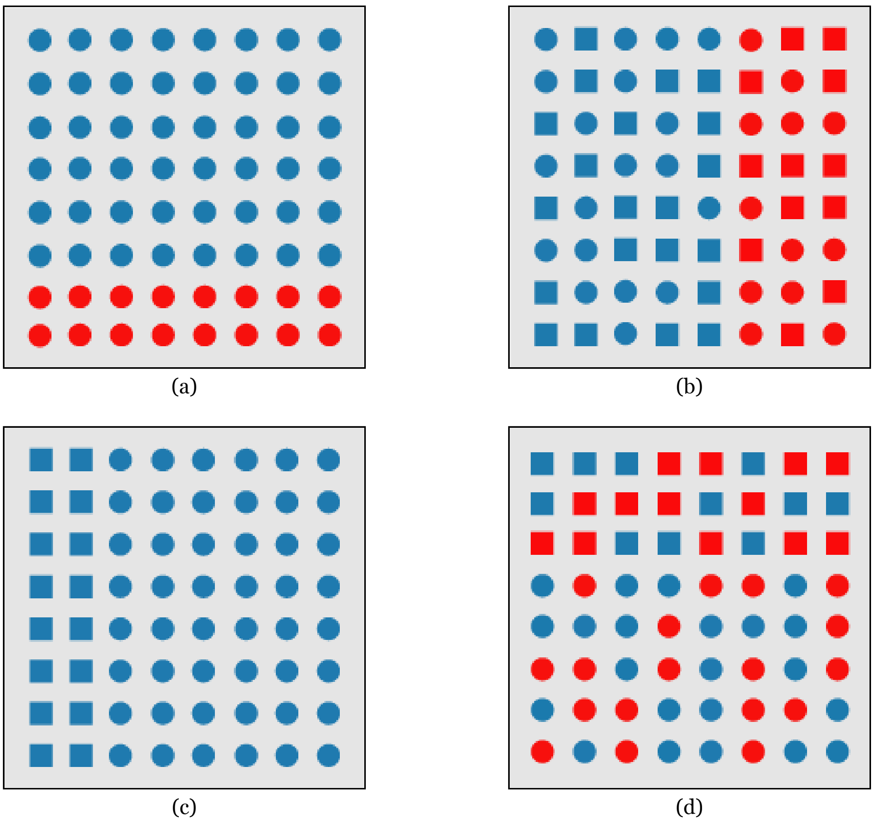
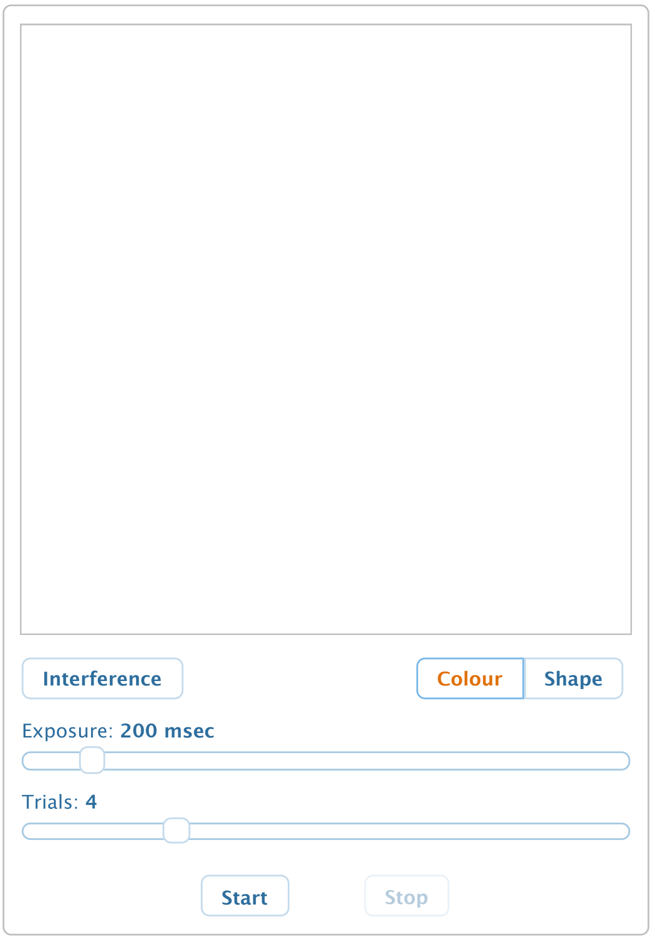


Fig. 14: An example of hue-on-form feature hierarchy: (a) a horizontal hue boundary is preattentive identified when form is held constant; (b) a vertical hue boundary is preattentively identified when form varies randomly in the background; (c) a vertical form bound-

ary is preattentively identified when hue is held constant; (d) a horizontal form boundary cannot be preattentively identified when hue varies randomly in the background

Callaghan also documented a luminance-on-hue preference during her experiments [Callaghan 84, Callaghan 89]. More recently, a hue-on-texture interference has been shown to exist [Healey & Enns 98, Healey & Enns 99, Snowden 98, Treisman 85]; random variations in hue interfere with the identification of texture patterns, but not vice-versa. These hierarchies suggest the most important data attributes (as defined by the viewer) should be displayed with the most salient visual features, if possible. The data-feature mapping should avoid situations where the display of secondary data values masks the information the viewer wants to see.

The Javascript applet below will let you experiment with the two different boundary identifications: colour and shape. As in Fig. 14, the boundary is either horizontal or vertical, defined by either colour or shape. The "Interference" checkbox enables interference; for colour boundaries, this means that the brightness of each element varies randomly, for shape boundaries the colour varies randomly. The "Exposure Duration:" slider lets you control how long each display is shown (anywhere from 100 to 1000 msec). The "Number of Trials:" slider lets you control how many displays you want to try. After each display, the applet will tell you whether the boundary was horizontal or vertical. This allows you to compare your answer with the correct answer for each display you see.



Change Blindness

Recent research in visualization has explored ways to apply rules of perception to produce images that are visually salient [Ware 2000]. This work is based in large part on psychophysical studies of the low-level human visual system. One of the most important lessons of the past twenty-five years is that human vision does not resemble the relatively faithful and largely passive process of modern photography [Pomerantz & Pristach 89, Treisman 85, Treisman & Gormican, Wolfe 94, Wolfe et al. 2000]. The goal of human vision is not to create a replica or image of the seen world in our heads. A much better metaphor for vision is that of a dynamic and ongoing construction project, where the products being built are short-lived models of the external world that are specifically designed for the current visually guided tasks of the viewer [Egeth & Yantis 97, Mack & Rock 98, Rensink 2000, Simons 2000]. There does not appear to be any general purpose vision. What we "see" when confronted with a new scene depends as much on our goals and expectations as it does on the array of light that enters our eyes.

These new findings differ from one of the initial ideas of preattentive processing, that only certain features in an image are recognized without the need for focused attention, and that other features *cannot* be detected, even when viewers actively search for these exact features. More recent work in preattentive vision has presented evidence to suggest that this strict dichotomy does not hold. Instead, "visible" or "not visible" represent two ends of a continuous spectrum. Issues like the difference between a target's visual features and its neighbours' features, what a viewer is searching for, and how the image is presented can all have an effect on search performance. For example, Wolfe's guided search theory assumes both bottom-up (*i.e.,* preattentive) and top-down (*i.e.,* attention-based) activation of features in an image [Wolfe & Cave 89, Wolfe et al. 89, Wolfe 94]. Other researchers like Treisman have also studied the dual effects of preattentive and attention-driven demands on what the visual system sees [Treisman 91, Treisman & Souther 86]. Wolfe's discussion of postattentive vision also points to the fact that details of an image cannot be remembered across separate scenes except in areas where viewers have focused their attention [Wolfe et al. 2000].

New research in psychophysics has shown that an interruption in what is being seen (*e.g.*, a blink, an eye saccade, or a blank screen) renders us "blind" to significant changes that occur in the scene during the interruption. This *change blindness* phenomena can be illustrated using a task similar to a game that has amused children reading the comic strips for many years [Rensink 97, Mack & Rock 98, Rensink 2000, Simons 2000]. Fig. 15 contains ten Quicktime movies that loop over and over; each movie is made up of two separate images with a short blank interval separating them. A significant change occurs between the two images. Run the movies and try to locate the change. Many viewers have a difficult time seeing any difference and often have to be coached to look carefully to find it. Once they discover it, they realize that the difference was not a subtle one. Change blindness is not a failure to see because of limited visual acuity; rather, it is a failure based on inappropriate attentional guidance. Some parts of the eye and the brain are clearly responding differently to the two pictures. Yet, this does not become part of our visual experience until attention is focused directly on the objects that vary.

The presence of change blindness in our visual system has important implications for visualization. The images we produce are normally novel for our viewers, so prior expectations cannot be used to guide their analyses. Instead, we strive to direct the eye, and therefore the mind, to areas of interest or importance within a visualization. This ability forms the first step towards enabling a viewer to abtract details that will persist over subsequent images.

Dan Simons offers a wonderful overview of change blindness in his introduction to the Visual Cognition special issue on change blindness and visual memory [Simons 2000]. We provide a brief summary of his list of possible explanations for why change blindness occurs in our visual system. Interestingly, none of these explanations by themselves can account for all of the change blindness effects that have been identified. This suggests that some combination of these ideas (or some completely different hypothesis) is needed to properly model this phenomena.

Airplane
[Quicktime | GIF]

Chopper and Truck
[Quicktime | GIF]

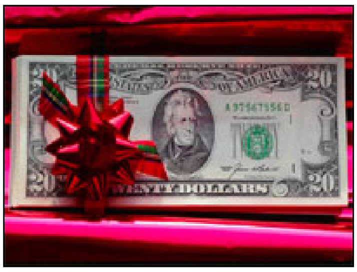
Corner
[Quicktime | GIF]

Dinner
[Quicktime | GIF]

Farm
[Quicktime | GIF]

Harborside
[Quicktime | GIF]

Market
[Quicktime | GIF]



Money
[Quicktime | GIF]

Sailboats
[Quicktime | GIF]

Tourists
[Quicktime | GIF]

Fig. 15: Examples of change blindness, each image sequence contains a significant variation across its two frames; click on the image to view the image sequence as a Quicktime movie (or choose GIF to view an animated GIF); all sequences courtesy of Ron Rensink, see his discussion of change blindness for additional resources

Overwriting

One intuitive suggestion is that the current image is overwritten, either by the blank between images, or by the image seen after the blank. Information that was not abstracted from the first image is lost. In this scenario, detailed change can only be detected for objects the viewer focuses on, and even then, only abstract differences may be recognized.

First Impression

A second hypothesis is that only the initial view of a scene is abstracted. This is plausible, since the purpose of perception is to rapidly understand our surroundings. Once this is done, if the scene is not perceived to have changed, features of the scene should not need to be re-encoded. This means that change will not be detected except for objects in the focus of attention. One example of this phenomena is an experiment conducted by Levins and Simon [Levins & Simon 97, Simon 96]. Subjects were asked to view a short movie. During a cut scene in the movie, the central character was switched to a completely different actor. Subjects were not told to search for any unexpected change in the movie (*i.e.*, they were naïve to the presence of the change). After viewing the movie, subjects were asked if they noticed anything odd. Nearly two-thirds of the subjects failed to report that the main actor was replaced. When queried, 70% of the subjects who failed to see the change described the central character using details from the initial actor, and not the replacement. This suggests that their first impression of the actors was the lasting one.

Nothing is Stored

A third explanation is that after a scene has been viewed and information has been abstracted, no details are represented internally. This model suggests that the world itself acts as a memory store; if we need to obtain specific details from the scene, we simply look at it again. A somewhat weaker form of this model suggests that some detail is preserved between scenes (*e.g.,* the details of the objects in the viewer's focus of attention). In this way, we are blind to change unless it affects our abstracted knowledge of the scene, or unless it occurs where we are looking in the scene.

Everything is Stored, Nothing is Compared

Another intriguing possibility is that details about each new scene are stored, but cannot be accessed until an external stimulus forces the access. For example, if a man suddenly became a woman during a sequence of images, this discontinuity in abstracted knowledge might allow us to access the details of past scenes to detect the change. Alternatively, being queried about particular details in a past scene might also produce the stimulus needed to access this image history. In one study, an experimenter stops a pedestrian on the street to ask for directions [Simons 2000]. During this interaction, a group of students walks between the experimenter and the pedestrian. As they do this, one of the students takes a basketball the experimenter is holding. After providing the directions, the pedestrian is asked if anything odd or unusual changed about the experimenter's appearance. Only a very few pedestrians reported that the basketball had gone missing. When asked specifically about a basketball, however, more than half of the remaining subjects reported it missing, and many provided a detailed description. For example, one pedestrian reported, "Oh yeah, he did have a ball, it was red and white." Not only was the pedestrian able to recall the presence of the basketball when prompted, he was also able to provide specific details about its unique appearance.

Feature Combination

A final hypothesis is that details from an initial view might be combined with new features from a second view to form a combined representation of the scene. Presumably, viewers would not be aware of which parts of their mental image come from the first scene, and which come from the second. The details being combined must make sense, and must be consistent with the viewer's abstract understanding of the scene, otherwise the change will be recognized "impossible" or "out of place".

More Recent Hypotheses

Simons and Rensink [Simons & Rensink, 2005] recently revisited the area of change blindness. They summarize much of the work-to-date, and describe important research issues that are now being studied using change blindness experiments. For example, evidence shows that attention is required to detect changes, although attention alone is not necessarily sufficient [Triesch et al. 2003]. Changes to attended objects can also be missed, particularly when the changes are unexpected. Changes to semantically important objects are detected faster than changes elsewhere [Rensink 97]. Low-level object properties of the same kind (e.g. colour, shape, etc.) appear to compete for recognition in visual short-term memory, but different properties seem to be encoded separately and in parallel [Wheeler and Triesman, 2002] (similar in some ways to Triesman's original feature integration theory [Triesman & Gelade 80]). Finally, experiments suggest the locus of attention is distributed symmetrically around a viewer's fixation point [Tse et al. 2003].

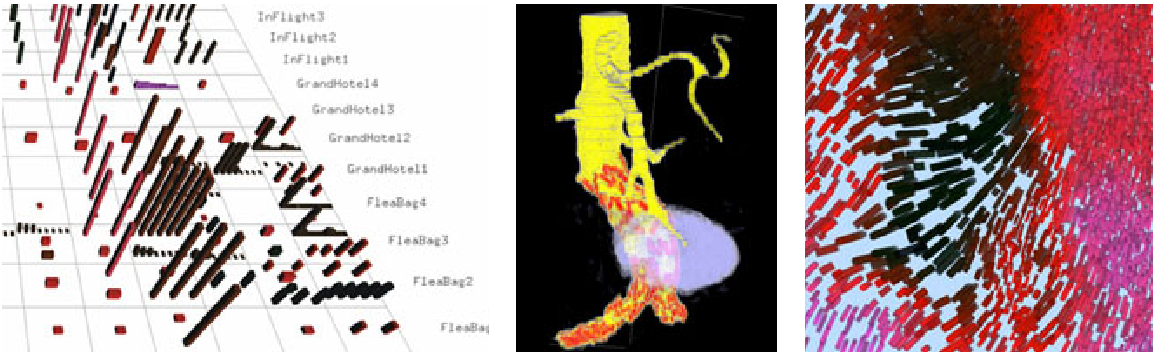
Simons and Rensink also described hypotheses that they felt are not supported by existing research. For example, many people have used change blindness to suggest that our visual representation of a scene is sparse, or altogether absent. Simons and Rensink present four hypothetical models of vision that include detailed representations of a scene, while still allowing for change blindness. A detailed representation could rapidly decay, making it unavailable for future comparisons; a representation could exist in a pathway that is not accessible to the comparison operation; a representation could exist and be accessible, but not be in a format that supports the comparison operation; or finally an appropriate representation could exist, but the comparison operation is not applied even though it could be. Simons and Rensink claim that, at the time of their article, these possibilities have not been conclusively ruled out, and therefore no conclusions about the sparseness of detail of our visual representations can be made.

Simons and Rensink conclude with a short list of areas for future research in change blindness:

- Can observers detect a change even if they fail to perceive it consciously (in other words. does a "gut instinct" exist for change in a scene)?
- How detailed are our visual representations?
- Can observers experience change before they can explicitly localize and identify it?
- How do long-term memory representations contribute to change detection?

Many of these issues are now being studied in the psychophysics and vision communities.

Perception in Visualization



(a) (b) (c)

Fig. 16: Examples of perceptually-motivated multidimensional visualizations: (a) a visualization of intelligent agents competing in simulated e-commerce auctions, *x*-axis mapped to time, *y*-axis mapped to auction (each row represents a separate auction), towers represent bids by different agents with colour mapped to agent ID, height mapped to bid price, and width mapped to bid quantity; (b) a visualization of a CT scan of an abdominal aortic aneurism, yellow represents the artery, purple represents the aneurism, red represents metal tynes in a set of stents inserted into the artery to support its wall within the aneurism; (c) a painterly visualization of weather conditions over the Rocky Mountains across Utah, Wyoming, and Colorado, temperature mapped to colour (dark blues for cold to bright pinks for hot), precipitation mapped to orientation (tilting right for heavier rainfall), wind speed mapped to coverage (less background showing through for stronger winds), and size mapped to pressure (larger strokes for higher pressure)

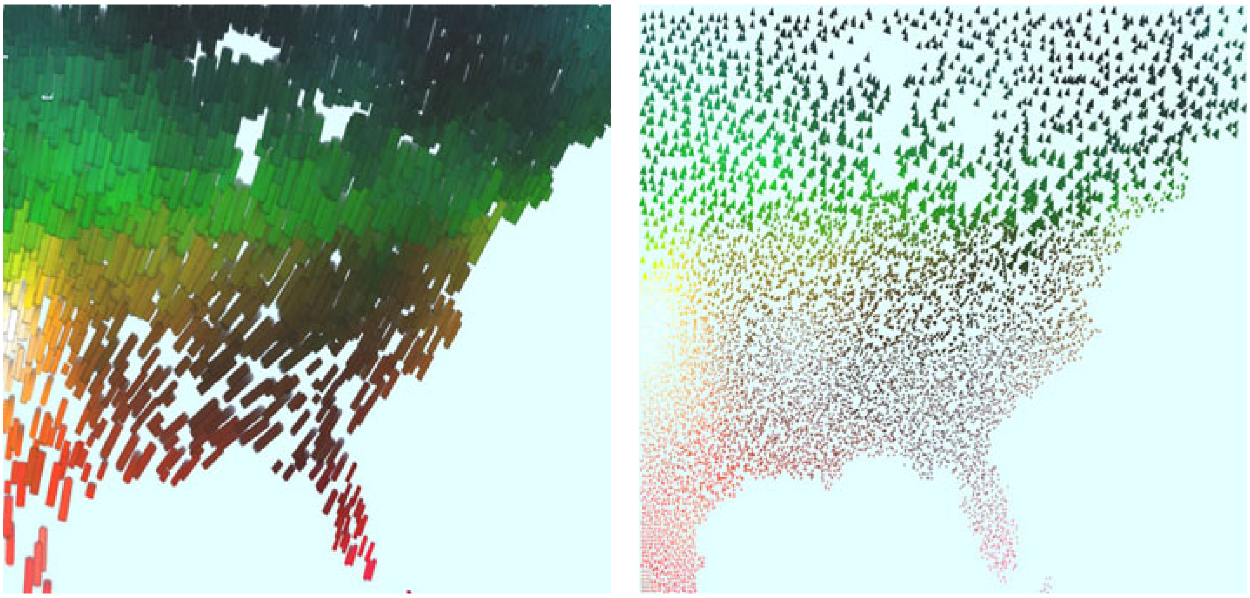
We conclude with some brief descriptions of how perceptual properties of colour, texture, motion, and nonphotorealism have been used in visualization.

Color

Color is a common feature used in many visualization designs. Examples of simple color scales include the rainbow spectrum, red-blue or red-green ramps, and the grey-red saturation scale [Ware 88]. More sophisticated techniques attempt to control the difference viewers perceive between different colors, as opposed to the distance between their positions in RGB space. This improvement allows:

- *perceptual balance:* a unit step anywhere along the color scale produces a perceptually uniform difference in color,
- *distinguishability:* within a discrete collection of colors, every color is equally distinguishable from all the others (*i.e.*, no specific color is "easier" or "harder" to identify), and
- *flexibility:* colors can be selected from any part of color space (*e.g.*, the selection technique is not restricted to only greens, or only reds and blues).

Color models like CIE LUV, CIE Lab, or Munsell can be used to provide a rough measure of perceptual balance [Birren 69, CIE 76, Munsell 05]. Within these models, Euclidean distance is used to estimate perceived color difference. More complex techniques refine this basic idea. Rheingans and Tebbs plotted a path through a perceptually balanced color model, then asked viewers to define how attribute values map to positions along the path [Rheingans & Tebbs 90]. Non-linear mappings emphasize differences in specific parts of an attribute's domain (*e.g.*, in the lower end with a logarithmic mapping, or in the higher end with an exponential mapping). Other researchers have constructed rules to automatically select a colormap for a target data attribute [Bergman 95, Rogowitz & Treinish 93]. Properties of the attribute like its spatial frequency, its continuous or discrete nature, and the type of analysis to be performed are used to choose an appropriate color representation. Ware constructed a color scale that spirals up around the luminance axis to maintain a uniform simultaneous contrast error along its length [Ware 88]. His solution matched or outperformed traditional color scales for metric and form identification tasks. Healey and Enns showed that color distance, linear separation, and color category must all be controlled to select discrete collections of equally distinguishable colors [Healey 96, Healey & Enns 99].



(a) (b)

Fig. 17: Historical weather conditions over the eastern United States for March, colour mapped to temperature (blue and green for cold to red and pink for hot), luminance mapped to wind speed (brighter for stronger winds), orientation mapped to precipitation (more tilted for heavier rainfall), size mapped to cloud coverage (larger for more cloudy), frost frequency mapped to density (denser for higher frost): (a) a nonphotorealistic visualization using simulated brush strokes to display the underlying data; (b) a traditional visualization of the same data using triangular glyphs

Our color selection technique combines different aspects of each of these methods. A single loop spiraling up around the L-axis (the luminance pole) is plotted near the boundary of our monitor's gamut of displayable colors in CIE LUV space. The path is subdivided into r named color regions (*i.e.*, a blue region, a green region, and so on). n colors can then be selected by choosing n/r colors uniformly spaced along each of the r color regions. The result is a set of colors selected from a perceptually balanced color model, each with a roughly constant simultaneous contrast error, and chosen such that color distance and linear separation are constant within each named color region (Fig. 17).

Texture

Texture is often viewed as a single visual feature. Like color, however, it can be decomposed into a collection of fundamental perceptual dimensions. Researchers in computer vision have used properties like regularity, directionality, contrast, size, and coarseness to perform automatic texture segmentation and classification [Haralick et al. 73, Rao & Lohse 93a, Rao & Lohse 93b, Tamura 78]. These texture features were derived both from statistical analysis, and through experimental study. Results from psychophysics have shown that many of these properties are also detected by the low-level visual system, although not always in ways that are identical to computer-based algorithms [Aks & Enns 96, Cutting & Millard 84, Julész 75, Julész 84, Julész 73, Julész 78, Snowden 98, Treisman 91, Wolfe 94].

One promising approach in visualization has been to use perceptual texture dimensions to represent multiple data attributes. Individual values of an attribute control its corresponding texture dimension. The result is a texture pattern that changes its visual appearance based on data in the underlying dataset. Grinstein et al. visualized multidimensional data with "stick-man" icons whose limbs encode attribute values stored in a data element [Grinstein 89]; when the stick-men are arrayed across a display, they form texture patterns whose spatial groupings and boundaries identify attribute correspondence. Ware and Knight designed Gabor filters that modified their orientation, size, and contrast based on the values of three independent data attributes [Ware & Knight 95]. Healey and Enns constructed perceptual texture elements (or pexels) that varied in size, density, and regularity [Healey & Enns 98, Healey & Enns 99]; results showed that size and density are perceptually salient, but variations in regularity are much more difficult to identify. More recent work found that 2D orientation can also be used to encode information [Weigle 2000]; a difference of 15° is sufficient to rapidly distinguish elements from one another. A follow-on to these studies showed that certain 3D orientation properties can also be detected by the low-level visual system [Liu et al. 2003].

(a) (b) (c)

Fig. 18: Examples of a natural brick texture applied to an underlying 3D object, oriented to follow different properties of the surface at a per-pixel level: (a) orientation follows a default "up" direction; (b) orientation follows the first principle direction; (c) orientation follows the second principle direction; all images courtesy of Victoria Interrante, see her discussion of texture synthesis for 3D shape perception for more information

Recent work by Interrante, Kim, and Hagh-Shenas has studied the use of different texture types and orientations for showing the shape of an underlying 3D object. Initial experiments investigated textures that varied in luminance (*i.e.,* greyscale patterns) [Interrante & Kim 2001, Interrante et al. 2002, Kim et al. 2003]. More recent work has studied the use of relief textures (*e.g.,* the brick pattern shown in Fig. 18). The textures were arrayed over the surface using orientations that were either isotropic (*i.e.,* all following a common direction, Fig. 18a), or anisotropic (*i.e.,* following different directions based on a property at that point on the surface, Fig. 18b, 18c). Preliminary results suggest anisotropic textures that follow both the first or second principle curvature directions produce surface perception that is as good or better than either principle direction alone, or than other orientation rules [Kim et al. 2003].

Motion

Motion is a third visual feature that is known to be perceptually salient. The use of motion is common in certain areas of visualization, for example, the animation of particles, dye, or glyphs to represent the direction and magnitude of a vector field (*e.g.,* fluid flow visualization). Motion transients are also used to highlight changes in a dataset across a user-selected data axis (*e.g.,* over time for a temporal dataset, or along the scanning axis for a set of CT or MRI slices). As with color and texture, our interest is in identifying the perceptual dimensions of motion and applying them in an effective manner. Three motion properties have been studied extensively by researchers in psychophysics: flicker, direction of motion, and velocity of motion.

For visualization purposes, our interest is in flicker frequencies F (the frequency of repetition measured in cycles per second) that are perceived as discrete flashes by the viewer. Brown noted that frequency must vary from 2-5% to produce a distinguishable difference in flicker at the center of focus ($1.02 \leq \Delta F \leq 1.05$), and at 100% or more for distinguishable difference in flicker in the periphery ($\Delta F \geq 2.0$) [Brown 65, Gebb et a. 55, Mowbray & Gebhard 55]. Tynan and Sekuler showed that a decrease in a target object's velocity or an increase in its eccentricity increased identification time [Tynan & Sekuler 82], although in all cases viewers responded rapidly (200-350 milliseconds for targets in the periphery, 200-310 milliseconds for targets in the center of focus). van Doorn and Koenderink confirmed that higher initial velocities produce a faster response to a change in the velocity [Hohnsbein & Mateeff 98, Mateeff et al. 95, van Doorn & Koenderink 82a, van Doorn & Koenderink 82b]. They claim this is due to the need for the target to traverse a "critical distance" before it can be detected. For a baseline velocity V_1 and a target velocity $V_2 = 2V_1$, approximately 100 milliseconds is needed to see the velocity change from V_1 to V_2 for slow V_1 (1° per second) and approximately 50 milliseconds for faster V_1 (2° per second or higher).

Researchers in psychology have used properties of motion to extend a viewer's ability to perform basic exploration tasks. Nakayama and Silverman showed that coherent motion or stereoscopic depth can be used to separate elements into coherent groups [Nakayama & Silverman 86], allowing viewers to search each group independently. For example, consider searching for a red circle in a background of red squares and blue circles, a situation that normally produces a time-consuming serial search for the target (Fig. 3). If the red elements are animated to move up and the blue elements are animated to move down, however, the target is immediately visible. Applying different motion patterns to the red and blue groups allows a viewer's visual system to separate them and search them independently, producing the rapid search for a curved element (a red circle) in a background of linear elements (red squares). Similar results can be achieved by displaying the red and blue elements on different stereoscopic planes. Driver et al. showed that oscillation can also be used to separate elements into independent visual groups, but only if the oscillation pattern is coherent [Driver et al. 92]. For example, a viewer could identify a red circle in a set of red squares and blue circles if all the red items oscillate up and down in lock step, and all the blue elements oscillate left and right in lock step. If the elements oscillate "out of phase", however (*i.e.,* some red elements start moving down while others are still moving up), viewers are forced to revert to serial search. More sophisticated motion patterns have also been analyzed, although with less success in terms of achieving high-speed search performance. Braddick and Holliday studied both divergence (*e.g.,* squares increase or decrease in size over a period of time, then snap back to their original size) and deformation (*e.g.,* rectangles deform from tall and skinny to short and wide, then snap back to their original shape) [Braddick & Holliday 1987]. Although the basic motion properties being shown can be rapidly identified in isolation, the combinations that form deformation and divergence were not detected by the low-level low-level visual system.

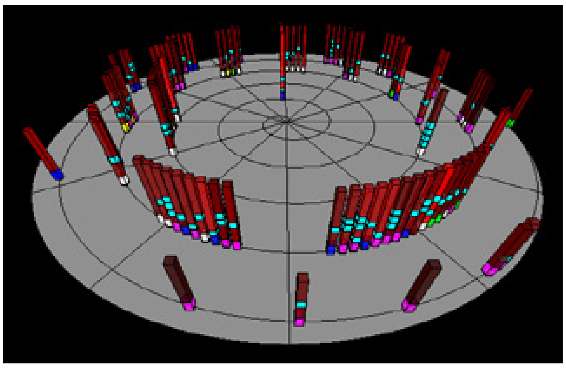


Fig. 19: An example of motion (animation) used to visualize location and membership of elements common across two queries into an underlying data source (click on the image to view a Quicktime movie of the animation sequence)

Properties of motion have been extended to visualization design. Animated motion is used in flow visualization to show the direction and speed of different flow patterns (*e.g.,* by Kirby [Kirby et al. 1999]). Kerlick proposed the use of animated glyphs to visualize 2D and 3D multidimensional datasets [Kerlick 1990]. He designed a set of "boids" to encode attribute values at specific locations in the dataset, for example, a sphere boid to query data values at a user-selected location, or pyramid and dart boids that animate over a vector field to visualize its shape. Bartram et al. studied the use of variations in color, shape, and motion to "notify" viewers while they were engaged in a separate, attention-demanding task [Bartram et al.

2002]. Results showed that applying motion to a static glyph was significantly easier to recognized, compared to changing the glyph's color or shape. This finding held both when the glyph was near the center of focus, and when it was located on the periphery of the viewer's gaze. The authors also studied how distracting a secondary motion cue was judged to be. Flicker was the least distracting, followed by oscillating motion, then divergence, and finally movement over long distances. Related work by Bartram et al. confirmed that different motion paths can be used to perceptually group glyphs in a manner similar to the work of Nakayama and Silverman or Driver et al. [Bartram et al. 2003]. The groups can then be searched independently for a target feature.

Nonphotorealism

For many years researchers in the areas of modeling and rendering in computer graphics have studied the problem of producing photorealistic images, images of graphical models that are indistinguishable from photographs of an equivalent real-world scene. Advances in areas such as the simulation of global light transport, modeling of natural phenomena, and image-based rendering have made dramatic strides towards achieving this goal. At the same time, researchers have approached the issue of image generation from a completely different direction. Although photographs are common, there are many other compelling methods of visual discourse, for example, oil and watercolor paintings, pen and ink sketches, cel animation, and line art. In certain situations, these *nonphotorealistic renderings* are often considered more effective, more appropriate, or even more expressive than an equivalent photograph [Gooch & Gooch 2001, Strothotte & Schlechtweg 2002].

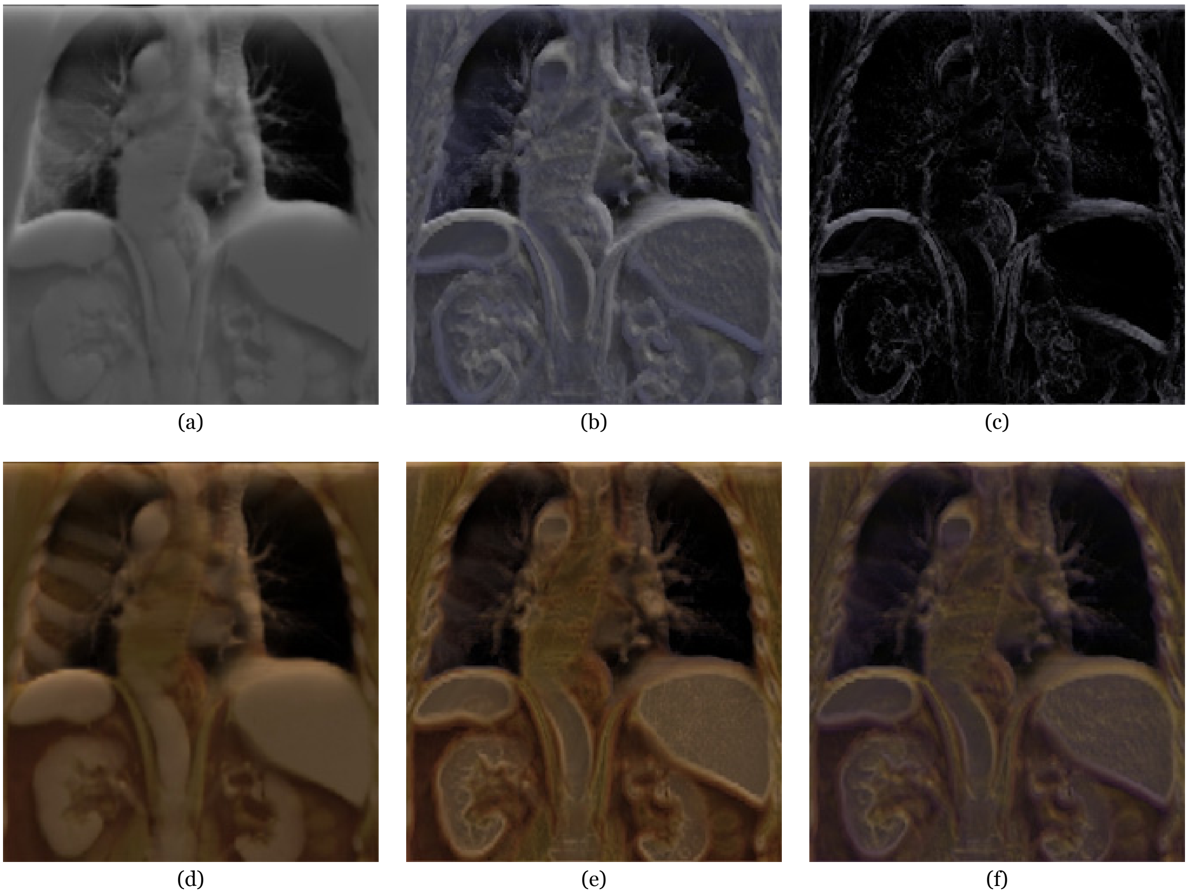


Fig. 20: Examples of nonphotorealistic enhancements for volume illustration: (a) original greyscale image of an abdominal CT scan; (b) the same image with tone enhancement applied; (c) with volumetric boundary sketching; (d) original colour image of the same abdominal CT scan; (e) with halos and boundary and silhouette enhancement; (f) with tone shading and boundary and silhouette enhancement; all images courtesy of Penny Rheingans, see her discussion of volume illustration for more information

More recently, researchers in scientific visualization have started to investigate how techniques from nonphotorealistic rendering might be used to improve the expressiveness of a data display. Laidlaw extended the layered approach of Meier [Meier 96] to visualize multidimensional data in a painterly fashion [Kirby et al. 1999, Laidlaw 2001, Laidlaw et al. 1998]. He varied style properties such as underpainting lightness and stroke size, transparency, direction, saturation, and frequency to display multiple layers of information in a single nonphotorealistic image. Interrante discussed constructing natural textures to visualize multidimensional data [Interrante 2000]. Ebert and Rheingans used nonphotorealistic techniques such as silhouettes, sketch lines, and halos to highlight important features in a volumetric dataset [Ebert & Rheingans 2000, Rheingans & Ebert 2001] (Fig. 20). Follow-on work applied stipple drawing techniques to interactively preview scientific and medical volumes [Lu et al. 2002]. Finally, research in our laboratory has identified a correspondence between image features detected by the low-level visual system and brush stroke properties employed by Impressionist masters during construction of their paintings [Healey et al. 2004] (Fig. 17). We exploit this correspondence to try to construct visualizations that are both effective and aesthetic.

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