THE EFFECT OF FAMILIARITY IN EARLY VISION:

LETTER PERCEPTION

by

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Abstract

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The effect of familiarity on early visual processing was examined with two letters, 'p' and 'b,' as instances of familiar stimuli, and two unfamiliar letter-like items, 'non-p' and 'non-b,' created by displacing the loops within the 'p' and 'b' to the left of the vertical lines.

The hypothesis was that there might be featural level interactions within familiar contexts (e.g., letters) rendering a line feature in a 'p' qualitatively different from the same line feature within a 'b.' Similar interactions would not exist for unfamiliar items, and therefore the line feature within a 'non-p' would remain the same as that of a 'non-b.'

For the 'line' experiments, tasks required subjects to find a longer line among arrays of shorter lines of equal length in one condition, or to find a shorter line among arrays of longer lines in another condition. For the letter experiments, the target was 'p' and distractors were 'b's, but the 'p' appeared in all arrays. The 'p' was longer or shorter than the 'b's in target-present arrays, and the same length as the 'b's in target-absent

arrays. The same configurations were used for the non-letter experiments with the 'non-p' and 'non-b' items.

For the short target conditions, overall the reaction time was faster for target-present arrays than for target-absent arrays in both the 'line' and the 'non-pb' arrays. For the long target conditions, the difference of reaction time between the target-present and the target-absent arrays was larger for the 'non-pb' arrays than for the 'line' arrays.

The search speed difference between the target-present and the target-absent arrays was in general absent for the 'pb' arrays when the targets were short items. If the target items were long, the search speed was slower for the target-absent trials than for the target-present trials, however still to a lesser degree than they were in the 'non-pb' arrays.

Therefore, for the short target conditions the 'non-pb' data patterns were similar to the 'line' data patterns, whereas the 'pb' data were qualitatively distinctive. For the long target conditions the evidence for qualitatively different lines in familiar stimuli was less clear.

Table of Contents

List of Tables

List of Figures

Introduction

There is a general agreement that "seeing" may be thought of as a two-step process. A visual experience is first analyzed into more elementary sensations and then these components are synthesized together into a complex whole object. A psychological model of the visual system, as in physiological observations of visual cortex, assumes the existence of specialized detectors that search for particular characteristics (features) of stimuli, such as line, color or orientation, in a very early stage of visual information processing.[1] The whole objects (conjunctions) are later constructed from such separate parts and matched against their internal representations in long term memory for recognition.

The two broad unresolved general issues in early vision processing then are what the components of visual object representations are and how those components are reassembled together to form integrated percepts. Humans are only consciously aware of the already constructed whole objects with immediate and effortless recognition. For instance, an "A" is perceived as a unified whole object and not a collection of two oblique lines and a crossing bar. Consequently, differentiation of component parts (features) as functionally separate units from their whole (conjunction) represents a

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[1] Although neuronal specificity of visual cortex for particular aspects of stimuli initially motivated and lend support to psychological models of feature detectors (Hubel and Wiesel, 1962), equivalence between such cortical cells and hypothetical units of features was soon rejected (Spoehr & Lehmkuhle, 1982).

difficult task. An intuitive sense of a feature, for example, a crossing line in "A," does not reveal much about its true feature status apart from the whole of "A" within the processing system. Nor does a subjective impression of the line as a component of "A" guarantee the existence of a feature detector in the visual system that is tuned to register that particular aspect of "A." To find out if the perceptual components indeed function as separate units, such impressions need to be translated into some type of behavioral (or physiological) measures that manifest differential responses towards features and their conjunctions.

Once features are registered and identified, the visual system has to assemble them to a holistic visual experience. One of the problems of the synthetic stage of visual processing would be to put the features together in their correct spatial relation to each other. The visual system should have a mechanism that regulates this assembly stage in such a way that the features do not end up as a jumble of randomly collected parts. However, the mechanisms by which the location information is to be linked to registered features are unknown, and it is difficult to obtain behavioral responses that can unambiguously be interpreted as reflecting the linking mechanism.

Some years ago, Treisman (Treisman & Gelade, 1980) proposed a model of visual perception that addresses these issues. Her "feature-integration theory of attention" is unique in its usage of attentional resource as a "binding agent" in the visual system. The model's basic claim is that attention integrates features into conjunctions. The traditional two stages of attentional resource allocation (Neisser, 1967), a preattentive stage of large capacity and an attentive stage of limited capacity, are applied to workings of the visual system in a rather straightforward manner. The detection of features over a given visual field can be processed at preattentive stage and therefore does not require attentional resource. However, to form conjunctions of features, attention is needed as a "binding glue." Consequently, conjunctions have to be processed at the attentive stage. Since the preattentive stage operates prior to deployment of attentional resources, processing can be performed in parallel; whereas processing at the attentive stage with its limited amount of resources, proceeds in a serial manner. Therefore, features are processed in parallel and conjunctions are processed serially. Features are registered early, automatically and in parallel across the visual field; and then as focused attention moves from item to item, the features within the "spotlight" of attention are conjoined to form a unified whole object. Once the features are integrated, the resulting compounds continue to be perceived and stored as such.

The model offers resolutions for the two issues introduced earlier, the differentiation of features from conjunctions and the mechanism of integration of features. Since different kinds of processes are involved in detecting the presence of features and conjunctions, differential behavioral responses to them can be generated by experimental manipulations. Only the features on which attention is focused are conjoined together, and this will prevent compounds from consisting of a random collection of unrelated features. Treisman's model launched a long and prolific line of research, and empirical indication of parallel processing became the most important evidence of feature status.

One of the characteristics of Treisman's feature-integration theory is that it is a strictly "bottom-up" system. A contact with memory, or top-down effect, can only occur at the conjunction level. A number of most elementary, primitive and separate feature detectors (or maps) operate at a very early stage of processing, and any perception of an integrated whole is a final outcome of a sequence of operations that were performed following this first stage. As such, the model's implicit assumption, like those of other feature analysis systems (Smith, E. E., & Spoehr., 1974; Smith, F., 1971; Spoehr & Lehmkuhle, 1982; Glass, Holyoak, & Santa, 1979; Wolfe, Cave, & Franzel, 1989), is that that there are only a limited number of fundamental features from which more complex representations are formed. Although no feature model has yet come up with a definitive list of primitive features, the assumption of a fixed number of feature detectors is essential. Without such a limitation, these models' distinction from template models of pattern recognition would be inconsequential.[a]

The assumption of a limitation in the number of primitive features also suggests that experience or practice should exert minimal influence in their existence. There would be two ways for such an influence to operate; one is through the modification, in some fashion, of the workings of the elemental feature maps themselves. The other would be by creating new features with accumulated exposure to the same type of visual patterns. In a model like Treisman's, since there is no specific mechanism that can alter feature maps' activation through practice, the influence of experience on basic units of perception could only be realized in the form of new features. On the other hand, although the model does not explicitly exclude the possibility of new features, features in general are viewed as having a primary, elemental and irreducible nature. There is an implied tendency to treat them as immutable and fixed components of visual architecture. By allowing creation of new features, such constructs would be made too flexible, perturbing many basic aspects of the machinery of feature models.[b]

The influence of experience, or familiarity, might have an effect in early vision if repeated experience with new compound features can have them "unitized," so that their conjunctions no longer require attention and consequently can be automatically registered (Laberge, 1973). Whether repeated exposure could "unitize" compound features is an empirical question.[2] Furthermore, even if the result were affirmative, such an allowance of "unitization" would considerably compromise the model's straightforward elegance. Since most of visual experience is indeed familiar, the model's theoretical distinction of features and conjunctions could not be tested in such familiar context. The differential, testable behavioral responses between features and conjunctions, the very factor that made Treisman's feature-integration model so interesting, would be difficult to utilize. In most of familiar contexts, features would have already reached the stage of "unitization," and consequently behavioral responses for those unitized features and conjunctions would be indistinguishable. To extend its logical consequence then, the model would only be useful for completely new and unfamiliar

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[2] As far as letters are concerned, when they were tested in Treisman's experiments (Treisman & Gelage, 1980), the unitization did not occur.

visual experiences. Therefore, it would be a fair characterization of the feature-integration theory of attention as it stands that the model does not accommodate top-down effects at a feature level.

Unlike Treisman's model, in which features and their relationship to conjunctions is consistent,[3] studies from another perspective (Garner, 1970; Garner, 1978; Melara & Marks, 1990d) have shown that not all features conjoin in the same manner. Some features are combined in such a way that their "ungluing" becomes very difficult or impossible (integral dimensions). A typical example is hue and brightness of a color patch. Subjects find it difficult to process the hue of a color separately from its brightness. On the other hand, other features, for instance, a size and a form, can easily be processed independently of each other (separable dimensions).[c] Such works therefore, when interpreted through feature models like Treisman's, suggest that there may exist some kind of unknown interactions between features and conjunctions; the path from features to conjunctions might not be as simple and uniform as Treisman's model implies.

Given that the feature-conjunction relationship may not be uniform across different kinds of visual dimensions, there is a theoretical possibility that the relationship could also be different in familiar and unfamiliar visual contexts. Unlike studies in dimensionality that were aimed to test a stimulus property as opposed to a response (or

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[3] Apparently, the only requirement of features for their eventual correct conjunction is that they should be within the same "spotlight" of focused attention.

perceiver's) property, familiarity is not a property of the visual pattern itself, but of subject's visual experience with that pattern. [4] In that sense, the issue of a familiarity effect in early vision is to ask how early in the visual system top-down processing starts to exert its influence. Memory contact, in feature analysis models of pattern recognition, occurs at the last step of processings, after features are encoded, assembled and integrated. On the other hand, if features could integrate in different manners depending on the familiarity of the context, the implication would be that the memory access or top-down effect can occur at a much earlier step, possibly even before the integration process begins.

This thesis examines the question in terms of whether familiarity can influence processings at a feature level specifically as configured in the feature-integration model. If a familiarity influence can occur at the feature level, then models like Treisman's would need modification that would allow top-down processing to exert an influence at a much earlier stage than in the system as currently described. The thesis specifically examines, through systematic manipulation of stimulus familiarity, one of the provisions of current feature models, namely, the independence among elemental features and their conjunctions. If familiarity effects occur very early in visual processing, then they may

[4] Integral/separable dimensions are properties of a stimulus and do not depend on a perceiver's response mode. For instance, as a psychological unit, color is one single thing and hue, saturation and brightness do not exist separately. It is not the subjects who are integrating the three dimensions. The dimensions themselves do not exist in the stimulus of color.

occur because of acquired non-independence of feature detectors in the system. A line detector in current models, for instance, is not affected by the workings of other feature detectors. In contrast, it is possible that activations of other feature maps might affect the line detector's operation in some fashion under some circumstances, and that is how familiarity could have its effect in early processing stages. This is a very tentative proposition. In the light of dimensionality data, however, that clearly indicate that features could conjoin in different ways, it is worthwhile to investigate the proposition within a different empirical framework. If a familiarity effect does not occur, then the result would strengthen the feature models' current principle of treating all features equally in early vision.

In this thesis, letters are used as examples of familiar stimuli and non-letters are used for unfamiliar stimuli. Treisman's research method was adopted without much change and experiments were conducted according to her framework.

Review of Literature

Features and conjunctions. In Treisman's feature-integration model (Treisman & Gelade, 1980), each feature module simultaneously extracts its features from objects in multiple locations in a visual scene (see Figure 1). All the features are initially registered preattentively in parallel. At the same time, a location map is generated; it registers all the locations for each object. These locations are connected to each feature in each feature map, though not yet integrated with the features to form whole objects. When Attention focuses on each location the features connected to the particular location are

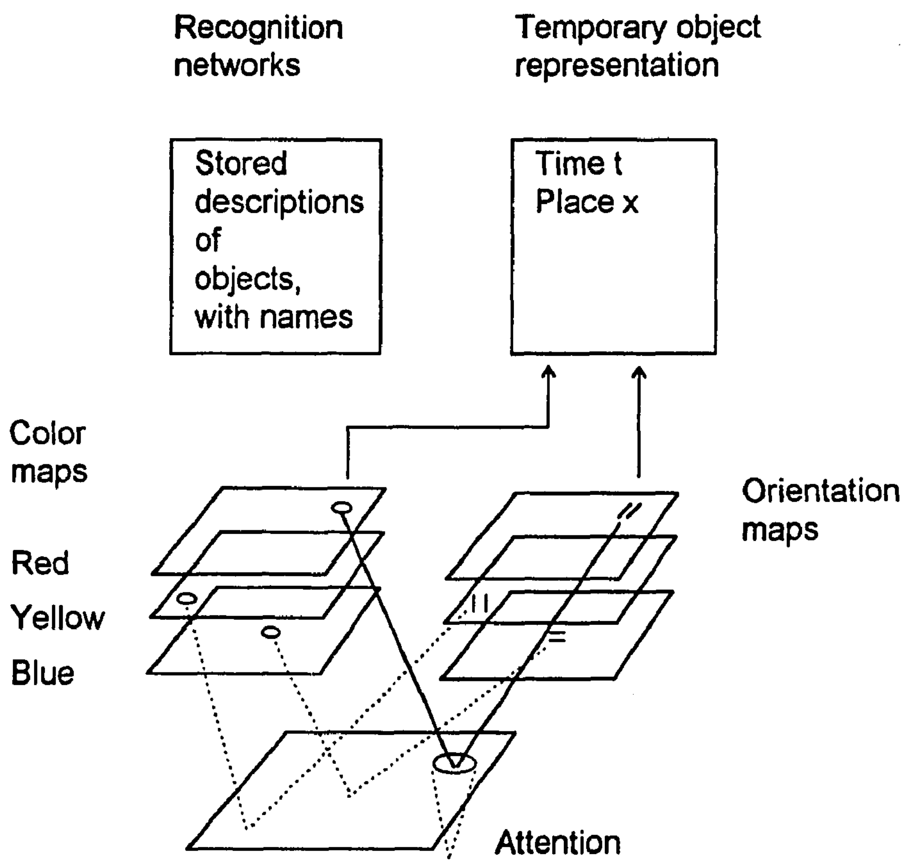

Figure 1. From "Features and objects: The fourteenth Bartlett Memorial Lecture" by Ann Treisman, 1988, *Quarterly Journal of Experimental Psychology*, 40A, p. 202.

conjoined, and the system matches the whole object against memory, and goes on to the next locations or initiates a response, as appropriate.

The model has been tested extensively with the methodology that was developed originally without much change to the present time. In the original set of studies, subjects saw arrays consisting of the letters X in green and T in brown on a tachistoscope. The number of X_{green} and T_{brown} stimuli presented on any given trial, that is, array size, was 1, 5, 15 or 30, chosen in a random order. There always was an equal number of X_{green} and T_{brown}. In feature search conditions, targets, which appeared in 50% of the arrays, were a blue colored letter or the letter S. In conjunction search conditions, targets were X_{brown} for some subjects and T_{green} for others. Thus, in conjunction search, subjects were forced to conjoin two features, color and shape, in order to find the target, whereas in feature search a detection of a unique feature was sufficient for required responses. Subjects always were instructed to respond as rapidly as possible, and pressed one button when they found the predesignated target and another button when they did not.

When reaction time was plotted against array size, slopes of the feature search tasks remained shallow, but conjunction search slopes increased linearly. Slopes for target-absent trials were either the same as or slightly steeper than those for target-present trials in feature search, but they showed a 1 : 2 ratio (target-present to target-absent) in conjunction search.

That reaction time in feature search did not change substantially with the addition of more distractor items indicates that the array items were processed in parallel. If they were processed serially, reaction time would have increased when the number of items to examine increased. When arrays are searched serially, as in conjunction conditions, the search is expected to end when the target is found (self-terminating search). For target-absent trials all items should be examined before the decision can be made (exhaustive search); when the target is present, only half of the total items, on the average, need to be examined. This search pattern will produce a 1 : 2 ratio of presence versus absence in slope (Sternberg, 1966; Treisman & Gelade, 1980). To summarize, single features can be found at a preattentive, parallel processing stage, and therefore their search slope in the target search task will be shallow. In contrast, search for conjunctions needs to be carried over to an attentive, serial processing stage, and therefore slope increases as array size increases.

A number of converging experimental results supported the model's validity. If the target was a unique feature, reaction time did not increase with the increasing array size and the feature target appeared to "pop-out" subjectively. This "pop-out" did not occur for conjunction targets; instead clear increases were seen in reaction time (RT) for larger arrays (Treisman & Gelade, 1980; Treisman, 1982; Treisman, 1988; Treisman & Sato, 1990).

As conjunctions of features require focused attention in this model, and as attention is a limited resource, when it is overloaded it should be possible to observe erroneous conjunctions. This in fact occurred. When presentation time was sufficiently brief or extra tasks had to be performed concurrently, subjects sometimes reported the presence of "illusory conjunctions." For example, from a display of T_{pink} and S_{brown}, subjects sometimes reported the presence of T_{brown} (Treisman & Gelade, 1980; Treisman & Schmidt, 1982; Cohen & Ivry, 1989; Cohen & Rafal, 1991; Fang & Wu, 1989; Tsal, 1989; Virzi & Egeth, 1984).

Another prediction of the model is that features should mediate texture segregation but conjunctions should not. Segregation of texture is an immediate, automatic and preattentional segmenting of a visual scene according to texture differences (Julesz, 1981). When two segregated areas were differentiated by features (for example, O_{red} and V_{red} in one side versus O_{blue} and V_{blue} in the other), segregation was fast and automatic. When they differed with respect to conjunctions (e.g., O_{red} and V_{blue} in one side versus O_{blue} and V_{red} in the other), segregation was slow and required focused attention (Treisman & Gelade, 1980; Folk & Egeth, 1989; Sagi & Julesz, 1985).

According to Treisman's model, search for a single feature could be achieved without knowing its location, but a conjunction target needs to be located because its feature integration does not occur until attention is focused on its location. Therefore, location information and feature search could be independent but a search for conjunction targets should be, and is dependent on correct location information (Treisman & Gelade, 1980; Nissen, 1985; Tsal & Lavie, 1988; Johnston & Pashler, 1990).

These results strongly supported Treisman's original model, but conflicting results soon were reported. One crucial prediction of the model is that conjunction searches should always be serial, but over the years, several instances were reported where conjunction searches did not result in linearly increasing slopes. When subjects searched for a conjunction O_{red} in a subset of three red colored letters, O_{red} and two N_{red}, varying the number of O_{black} items added to the subset did not change the search rate (Egeth, Virzi, & Garbart, 1984). Subjects were able to limit the search within the subset of red color. Pashler (1987) used a set of stimuli similar to Treisman's, and found that when the display size was less than 8, the search for conjunctions was parallel. The finding indicates that all that distinguishes parallel search in experiments of features and conjunctions may be the maximum size of the display beyond which serial search occurs.

Nakayama and Silverman (1986) found that the conjunction of stereoscopic depth and motion can be detected in parallel. When stimuli were stereograms consisting of two planes, with all items in the front plane moving up and all items in the back plane down, to find a target moving in the opposite direction in either plane (that is, a conjunction of depth and motion) was completed in parallel. When the front plane was of all blue items and the back plane of all red items, the search for a red in the front plane or a blue in the back (a conjunction of depth and color) was also based on parallel processing. Another group found that motion and form can be searched in parallel (McLeod, Driver, & Crisp, 1988). In a display of Xs and Os randomly dispersed, if all Os move upwardly and Xs remain static, the time to detect the moving target X is not affected by display size. It seems as if all randomly dispersed moving objects can be segregated from static ones and the search can be confined to moving items only.

The problem of the fast search for conjunctions can be resolved by modifying the strict requirement in Treisman's original model that search for conjunctions must be serial. In this modification, instead of searching array items one by one, items can be grouped and the search can then proceed group by group while maintaining parallel search within each group (Treisman, 1982). This will reduce slopes of reaction times for conjunction searches as array size increases.

Treisman's recent "pooled response model" (Treisman & Souther, 1985; Treisman & Gormican,1988) presented detailed accounts of how this grouping can be carried out when a single feature map's activity is involved. Rather than searching through individual array items, subjects check a pooled response from the relevant feature map for the presence of activity anywhere in that map, independent of spatial locations. To decide whether a target is present, subjects compare activities in the pooled responses of a display containing a target and of a display of the same size containing only distractors. If the difference between the two measures of pooled response is large enough, search can proceed in parallel. However, the difference between the displays will decrease as the number of distractor items increases, and once preattentive differentiation between the two classes of arrays becomes unreliable, then subjects would be forced to search serially.

For instance, if a display of three distractors plus the target was just discriminable enough from a display of four distractors, the same magnitude of difference (between the two displays) will not be large enough to differentiate two displays of 12 items (target display and distractor display) based upon their pooled activity levels. Either subjects will make more errors, or they will have to restrict the search group size to one that will permit the given target feature to emerge over distractor background noise. Subjects will have to search serially for these larger displays, not necessarily item by item, but group by group, with group size being a function of at least two variables, the tolerable level of error and saliency of the target item. Thus the number of subset sizes, and consequently the search speed, is dependent on the size of the difference between the two measures that is necessary for reliable responses. This topic is further discussed later in the section on search asymmetry.

The consequence of the revisions in the model is that processing at the feature map level is no longer always parallel. Exclusively parallel processing, rather than being a general property for feature level processing, became possible only for the case of a single unique feature in the whole visual scene. Just as the examples of parallel processing of conjunctions were found as introduced earlier, feature processings too became serial if multiple instances were involved. Thus the two most important principles of the feature-integration model, namely, the serial search of conjunctions and the parallel search of features, now seem to need some provisions to be applied to general workings of early vision.

Along with the limitations of the simple formula of feature search, a division between preattentive and attentive processing became much less distinct in the new model. The sharp dichotomy, which determined when the parallel or serial processing occurs, has now been blurred. Preattentive and attentive stages have now become reformulated into widely distributed versus narrowly focused attentional processes. Breadth of attentional focus determines accurate discrimination of features and correct conjunction of them. Depending on the needed level of accuracy and target distinctiveness, the "spotlight" of attention can vary along a continuum ranging from the entire display to a single item. If a target has a unique feature, or the difference between a target and distractors is very large, widely distributed attention would be enough for correct judgment, whereas finer discrimination between stimuli would require reduced attentional area.

Duncan and Humphreys (1989) presented a different theory of visual search that emphasized the similarity of distractors and targets. Their "similarity surface model" explains the reaction time differences between feature and conjunction searches as a grouping difference based on similarities between distractors and the target. The extent of similarity between the target and distractors, and among distractors themselves, determines the speed with which the target can be found. If the target is very different from distractors, then regardless of the distractors' similarity among themselves, the target "pops-out." On the other hand, if the target is similar to distractors, the degree of the similarity among distractors determines search efficiency. If distractor-distractor similarity is high, then search slope increases only moderately with increasing array size, whereas if it is low a much slower serial search is necessary. Therefore, search speed is not so much dependent on features and conjunctions, or parallel and serial processing, but rather on the dynamics of groupings based on similarity of items.

In Treisman's original data then, an X_{green} target among T_{green}s and X_{brown}s is detected slowly since the target is very similar to distractors of either type. It shares one feature with distractors while distractors themselves are very different because they do not have common features. On the other hand, blue color or shape S is so different from the distractors, that the degree of heterogeneity in distractors does not affect the search function and the search is rapid.

A qualitative difference between feature search and conjunction search is also contradicted by another alternative model (Wolfe et al., 1989). Their "guided search" model uses the output of a preattentive, high capacity, and parallel analysis to guide a slow, limited capacity and serial search stage (Cave & Wolfe, 1990; Wolfe, 1992; Wolfe & Cave, 1990; Wolfe & Friedman-Hill, 1992; Wolfe, Cave & Franzel, 1989). This connection between two stages is notably absent in Treisman's model.

In Wolfe's model the parallel stage has two components; top-down and bottom-up. A top-down mechanism obviously requires knowledge of the identity of the target item, and a bottom-up mechanism is strictly stimulus driven. Each feature map generates its own activation map based on the workings of these two components. The top-down process, with its knowledge of the target item, excites target items and non-target items differentially in each feature map. The bottom-up processing computes each item's similarity value based on its difference from other items for that particular feature.[5] Thus, during preattentive analysis, each feature module has two sources of activation, one from the top-down and the other from the bottom-up. After activations are calculated for each map, they are summed to produce a single overall activation map. This map goes to the next, serial stage. The serial process chooses the highest activation in the overall activation map.

To illustrate, if a target is a red vertical line among equal number of two kinds of distractors, a red horizontal and a green vertical, two feature maps, color and orientation, generate their activation maps. In the color module, top-down source excites red items more than green items. Its bottom-up source excites both colors equally; when half of the items are red and the other half is green each item's color similarity value is the same. The same type of computation is applied in an orientation module. When the two sources of activation are summed up, a half of the items in each module (red items in color map, vertical items in orientation map) has higher activation than the other half because it matches the target feature (their activation from bottom-up source is the same).

Finally an overall activation map is generated from the sum of the two modules. On this map, the target is the only item that has both features; red color that has higher

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[5] In their computational model (Cave & Wolf, 1990), for example, each item's bottom-up color value is determined by summing up the item's difference from every other item and dividing the sum by the total number of items. The result then is used as an exponential function (so that the item's activation gets even larger if it is large).

activation than green color and vertical orientation that has higher activation than horizontal orientation. All other items (distractors) have either one of these high activations but not both. When the serial stage is ready to start to process a new element, it can detect the target item easily since it has the highest activation in the activation map.[d]

Therefore, if the target is X_{red} among X_{green} and O_{red} distractors, the top-down process will have the color map excite all red locations and have the shape map excite all X locations within each feature map. The bottom-up process will excite all locations of X, O, red and green equally (because their similarity values are equal to each other) for each feature in their feature maps. At the serial stage, the master map's configuration contains all red locations from color map and all X locations from shape map. Because they are at separate locations, each location is excited only once except for the target location that has activation from both red as well as X. As a consequence the target location is doubly excited. At this point, if there is no noise, attention can directly focus on the doubly excited location and the target can therefore be detected immediately, eliminating any need for serial search.

The system noise does not affect feature search[6] strongly, since the bottom-up activation of the target item, if it has a unique feature, is large enough to override the noise quickly. On the other hand, the target item's advantage over distractor items in conjunction searches (where each feature has the same number of occurrences) comes from the top-down activation. For instance, the target X_{red} has two sources of top-down activation whereas distractor items have only one. This advantage is rarely as large as the advantage of the strong bottom-up activation in the feature search case. As a consequence, noise is more likely to cause attention to be misdirected to non-target items in the search for conjunction targets compared to feature targets. In this model then, search time differences result from inherent system noise,[7] or the effectiveness of guidance. The reason that conjunction search is serial is not because of a binding operation that requires attention, as Treisman suggested originally, but because the configuration of the search condition makes it easy for the noise to mask the target items' activation.[e]

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[6] The target selection of feature search condition is not made in the parallel stage as in Treisman's model. Both the feature and the conjunction targets move over to the serial stage for selection and response processes. Thus, there is no qualitative difference between the two searches and the same machinery operates in the same manner. The difference in search speed solely comes from the different activation levels in the final activation map.

[7] Guided search model makes no commitment to the origin of the noise. It could be from any number of sources, the input to the parallel stage, the feature maps themselves, the overall activation map, the transfer from the parallel to the serial stage, or some combination of those.

Also, the model accommodates a top-down processing effect in the very early stage of visual perception by allowing the feature maps to be directly influenced by prior knowledge of the target. When the system knows the nature of the target, that knowledge can directly constrain the activation level of feature maps.

Search asymmetry. Search asymmetry refers to a phenomenon where the presence of a feature "pops-out" but its absence does not. A target defined by a unique feature usually is different from distractors because it possesses a unique feature that distractors do not, but it can also be different from distractors because it does not have a single feature that all distractors do. In either case, the target is different from the distractors by a single feature, but the search for the presence of the unique feature can be parallel whereas the search for its absence requires a serial process (Treisman & Souther, 1985; Treisman & Gormican, 1988). Treisman's "pooled response model" predicts this asymmetry and she provides ample empirical support (Treisman & Gormican, 1988).

There is a significant difference between detecting the presence of a feature versus its absence. For example, to find a circle containing an intersecting bar among empty circles, two pooled measures of the bar feature map, target-present and target-absent, are compared (see Figure 2). This comparison is always one bar versus none, regardless of the number of distractors, permitting the single bar to pop out. However, finding an

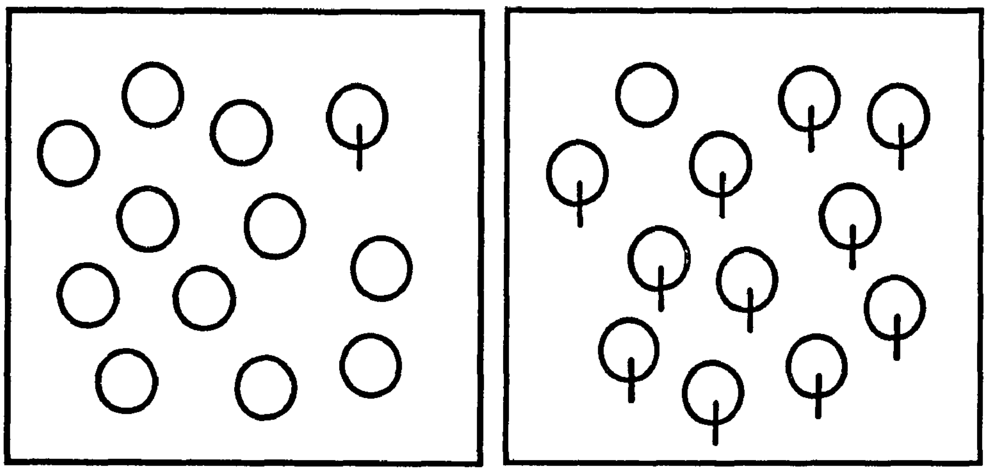

Figure 2. Examples of targets defined by the presence or the absence of a bar feature, from "Search asymmetry: A diagnostic for preattentive processing of separable features" by Ann Treisman, 1985, *Journal of Experimental Psychology: General,* 114, p. 289.

empty circle among circles with bars requires the much more difficult comparison of N versus N-1 bars, the two pools corresponding to the target-absent and the target-present conditions. Consequently the search has to be carried out by clusters, leading to slower reaction time as array size gets larger. Treisman and Souther (1985) found that the search slope for the empty circle was 20 ms per item for target-present trials and the ratio was 1 : 2 (positive : negative); while the search for the barred circle target produced a slope less than 4 ms for both target-present and target-absent searches.

The model takes consideration of this asymmetry further. "Present-absent" could be conceptualized as two ends of a continuum. If this is correct, just as the search for "presence or absence" of a feature produces the asymmetry, so should the search for targets defined by "more or less" of the same feature. Treisman and Gormican (1988) tested this prediction with many features. One particular feature, line length, whose configuration is a basis of the present experiments, is discussed below.

"More or less," in this case, is the amount of line length as it is defined operationally within experimental contexts. In one condition, a long line can be defined as a target among shorter lines of fixed length as discussed by Treisman and Gormican (1988). The search speed was 7.6 ms per item when the target was present, and 15.5 ms when it was absent. The converse experiment reversed the line lengths for target and distractors; the short line became the target and long lines became distractors. The search slope for target-present trials was now 14.3 ms per item, and 28.3 ms per item for target-absent trials. Thus, as in the case of "presence or absence" of a feature, to find "less" of a feature was more difficult than to find "more" of the same feature.

The absolute amount of the difference between the two pooled activations (target-present and target-absent) is the same when the target has "more" and when it has "less" of the line feature as they merely reversed the lengths of the target and distractors. It is the same magnitude of the difference in activation whether the difference is between a display of short lines and a display that has one of the lines longer (long target), or between a display of long lines and a display that has one of the lines shorter (short target). In either configuration, the difference between the two pools (target-present and target-absent) comes from the existence of a single target whose line length is either longer (long target) or shorter (short target) than the distractors.

However, that same difference (of target-present and target-absent) is compared with stronger distractor activations when the target is short than when it is long. This is so because the target-absent trials (with which the difference is compared) in the short line target conditions have long line distractors whereas they have short line distractors in the long line target conditions. According to Weber's law, the same value measured against the stronger background should be perceived as less salient than when it is measured against the weaker background. Therefore, the same magnitude difference between the target-present and the target-absent trials would be perceived as less distinct in the short target condition (because it is measured with the strong pool of target-absent trial) than in the long target condition (because it is measured with the weak pool of target-absent trial). To make the (perceived) small difference of the short line target conditions the same (perceived) magnitude as in the long line target conditions, the short line target condition's items need to be sub-grouped. This grouping will increase the search time of the short line target conditions. In other words, a short line is harder to find not because it is merely shorter than distractors, but because distractors are longer in this condition than they are in the long line target condition.

Treisman found that there exists this asymmetry over a variety of different features: longer line length, higher frequency (two objects versus one), contrast between color values (dark gray versus darker gray), curvature among straight lines, and skewed line among upright ones. To find "less" among "more" was always more difficult than the other way around.

Letter features. In Treisman's 1980 paper, a serial search function was found for the target letter R among distractor letters P and Q, but when the distractors were P and B the search appeared to be parallel. In the R/PQ set, the diagonal line common to R and Q appeared to be a separate feature that could float around freely if attention was overloaded because at the preattentive level its location information was not yet integrated. Because this diagonal can erroneously conjoin with P to make an illusory "R," reaction time will be slow to prevent that error. This slowing is not necessary in the R/PB arrays where no diagonal other than one in the target is present. Because finding R among Qs only was much faster than finding R among Bs only, this reversal of search speed followed by adding the same P to both conditions generated considerable interest.

Briand and Klein (1987) sampled two letters from the R, Q, B, P set and had subjects press a key when they detected an R. Attention was controlled by precuing the left or right side of a fixation point and making fifteen percent of the cues invalid. If stimuli containing P and Q can generate an illusory R and consequently need more attention to prevent this error, then the PQ condition has to benefit more from valid cues and suffer more from invalid cues than does the PB condition. When PQ and PB were presented in separate blocks a clear difference appeared.[8] PQ was slower for invalid cues and faster for valid cues compared to PB. These results indicated that the oblique line in R may be a separate feature and letters are not mapped directly onto unitary detectors (Laberge, 1973).

Duncan and Humphreys (1989), based on their search model introduced earlier, tried to modify the similarity level of the RPQ set by eliminating common components. If R and P are rid of their loops (), target-distractor similarity is greatly reduced. Search for R among Ps and Qs (R/PQ) was again associated with serial, self-terminating search, but search for the loopless R among lines and Qs () was parallel. If slow search speed were dependent on the conjunction R originally, the search in the loopless condition should also have been slow since the presumed cause for the slow search is the same in both cases. The diagonal line in the Q can move to the I and make it the loopless R in the modified condition just as it can move to P and make it

[8] There was no difference when PQ and PB were presented within the same block.

the target R in R/PQ condition.[9] Therefore, according to Duncan and Humphreys, the slow search of R among Ps and Qs was not due to the prevention of the illusory conjunction, but to the similarity of the target R to distractors P and Q.

Thus, as far as the letter set RQPB is concerned, the studies seem to converge on the conclusion that letters are not perceived as whole units.

However, there are different findings when letter sets other than RQPB were used. Duncan (1987) replaced a horizontal line in the letter "L" and a vertical line in another letter "L" with curvatures in such a way that illusory conjunctions of those lines from the two modified letters should form the genuine "L." When attention was overloaded subjects did not perceive the illusory "L." The probability of false alarms for the target letter L was the same 0.4 when the display elements were like , where the illusory conjunction was possible, and when they were like , where the illusory L can not be formed.

Humphreys, Quinlan and Riddoch (1989) found that an upside down T among upright Ts can be found in parallel, whereas detection of the same upside down T among Ts that have 4 orientations required serial search. The result supported their model that what determines search speed is similarity relations among items and not feature-conjunction differences.

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[9] The dispute is not for the unitization of the letter R. Since the loopless R which requires the same kind of conjunction can be searched in parallel, the determining factor is argued to be "similarity" and not the conjunction. Therefore the differential search speed cannot be used for or against the unitization of the R.

Pashler and Badgio (1985) presented a target "E" tachistoscopically among the distractors "F" and "L." Thus, an illusory E could be created with F and a horizontal line of L. The target was always present in one of 4 positions of a 2 × 2 matrix, and the task was to report its location, which should be always available at the correct conjunction. They found that the accuracy of location was the same at exposure duration of about 66 ms in both simultaneous and successive conditions, in direct conflict with Kleiss and Lane (1986) who found a higher error rate in the simultaneous condition using the RQPB stimulus set. Based on Treisman's feature-integration model, by having the subjects report the locations, the danger of potential illusory conjunction was eliminated and the correct identification of the target letter was assured.[10] That even in this strict condition, the simultaneous presentation resulted in localization as accurate as with successive presentation indicates that the conjunction search did not require any extra resources. In other words, unlike Treisman's claim (Treisman & Gormican, 1980) that the letter R required allocation of attentional resources (either for a binding process to operate or to prevent illusory conjunctions), the letter "F" was identified relatively capacity-free.

Probably the strongest evidence for global letter perception in this framework is findings of whole letter migration in search tasks. If a letter is a conjunction of lines, curves, junctions, etc., overloaded attentional capacity should produce migration of a

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[10] Since attention integrates features by focusing on locations (see Figure 1), correct report of items' locations means that the relevant features were correctly conjoined.

feature or features, but not an intact whole letter. However, migration of whole letters is in fact observed. In a display of "SAND LANE," if "L" is a conjunction of a horizontal line and a vertical line, it should be difficult for both lines from "LANE" to float away toward "AND" and generate the illusory word "LAND." But subjects report such letter migrations (Mozer, 1983; McClelland & Mozer, 1986; Treisman & Souther, 1986). It might be that letters are conjunctions of features but identification of individual letters in reading words is optional. If words have their own features, then they could be identified without going through steps for identification of component letters first. Such a possibility was raised by Treisman and Souther (Treisman & Souther, 1986) in accordance with earlier works (Johnson, 1975; Laberge, 1976), but remains unresolved.

If word level has its own features, bypassing the intermediate letter level, illusory words can arise because of these word feature exchanges. This feature-analytic (as opposed to letter-analytic) model of word identification has two variations that are not always differentiated (see, for example, Smith 1971). The first is that both letters and words employ the same kind of features; both words and letters are compounds of the same smaller components, except that the conjunction process is applied at different scales—on letter units or on word units. This argument does not seem to have explanatory power because feature models do not commit themselves to different scales of conjunctions. It would not matter whether the features of "L" are conjoined as two parts of the letter, or as the two parts of the word "LANE." The problem of the migration of "L," that is, the simultaneous movements of two features with their correct spatial arrangements, would remain the same even if the two features are conjoined at the word level.

The second version of feature analytic word identification is that a word has its own features distinct from its component letter. For example, "a concave boundary to the right-hand end" could be a word feature whose conjunction with other word features would build the word "FOX" (Treisman & Souther, 1986). If such word features exist, then one of these features in "LANE" may erroneously conjoin other features in "SAND" to become "LAND" just as the diagonal line in "Q" can conjoin "P" to become "R."[11] In other words, the "L" is not a perceptual unit but still a conjunction of features; only the "L" features are not involved in the analysis of SAND/LANE and instead the words' own features are joined. This seems to be an awkward solution. What it means is that the visual system processes objects at the lower, simpler level (letter) as compounds of separate, elemental and primitive features, but at the same time the system developed new features for those at the higher, complex level (word). Features that are related to "wordness" of a visual pattern would certainly involve much more complicated visual attributes and many more of them[12] would be required than letter features would. If such

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[11] It should perhaps be acknowledged that word features in "SAND/LANE" that could generate the illusory "LAND" are not so obvious as are the features in the case of "R/PQ" set and as a consequence more difficult to envisage or understand. In other words, as a theory, it lacks the elegance of "feature analyses of letters," which may not be a trivial point.

[12] A theoretical burden of a feature model is increased from constructing a feature list for 26 letters to that of 50,000 words.

"word features" exist, then it seems only reasonable to posit the existence of more local "letter" features.[f]

Thus, positing word features does not seem to bear direct relevance on the question of letter features. If word features are the same as letter features, it can not explain the phenomenon of letter migration any more than letter features could; if words have their own features, the fact alone can not exclude the existence of letter features for the reasons discussed above.

Any theory that proposes letters as conjunctions of features has to account for a number of well-established findings from the early studies. These works compared search speed or accuracy under the two conditions of simultaneous and successive presentation. If letters are conjunctions, therefore require allocation of attentional resources, then search for letter targets should result in better performance in successive than in simultaneous presentation condition. The simultaneous condition has more items to process within a given period of time, and therefore, less resource to expend per item, than the successive condition does.

For example, Eriksen and Spencer (1969) presented a target letter "A" with distractors "T" and "U." Array size was 1, 3, 5 or 9 and each item was presented one at a time for 2 ms in circular positions. Each array was presented at intervals of 5, 15 or 30 ms. The different interval times had no effect on their subjects' performance. Conjunction of letter features which needed attentional resource would have benefited from longer intervals. Shiffrin and Gardner (1972) found their subjects could decide whether a four item display contained "T" or "F" just as accurately in simultaneous presentations (of all 4 items) as in successive presentations (of one item at a time over a 50 ms duration). If one assumes that letters are conjunctions, the results could be interpreted as feature detections rather than letter detections because the targets did have unique features. But there is evidence that target items were not just discriminated from distractors, but completely identified. Subjects could identify the highest digit and its location among 4 randomly picked numbers just as well in a simultaneous condition as in a successive one (Pashler, 1987; Pashler & Badgio, 1985). To report the highest digit, which changes in every trial, all four numbers have to be identified. No single feature difference is enough to identify the target or its location.

Most of the evidence that supports the notion of holistic perception of letters is obtained through differential performance in simultaneous/successive presentation, whereas evidence against it is from reaction time with simultaneous presentation alone. Whether these two different methodologies are the cause of the conflicting results remains to be investigated.

Integral-Separable dimensions. Phenomenologically, hue and value of a Munsell chip are seen as one unitary thing whereas size and brightness of a square are seen as distinct and separate things. The nature of dimensional interactions in the two stimuli is different; hue and value are integral dimensions whereas size and brightness are separable ones. Integral dimensions are initially perceived as a dimensionless holistic blob and constituent dimensions can be differentiated only with effort. In contrast, separable dimensions are perceived as perceptually distinct components and subjects can easily process one component independently of another (Garner, 1970; Garner, 1974; Garner, 1978; Lockhead, 1972; Lockhead, 1979).

A general method that has been used to examine whether dimensions are integral or separable is to test whether selective attention to a single dimension is possible. If it is not possible, it means the system has that dimension "glued" to other dimensions rather than as a separable component. For example, can a subject attend only to hue in a color patch filtering out brightness or vice versa? Operationally, selective attention has been measured by employing speeded classification tasks. Fast reaction times to classify stimulus cards into different groups defined by different dimensions were used as an indication of selective attention.

Garner and Felfoldy (1970) asked subjects to classify color patches that could have two values of two different dimensions, hue (H_1 and H_2) and brightness (B_1 and B2). There were three classifications. Classification of two patches with the same brightness but different hue (e.g., H_1B_1 and H_2B_1) gave the baseline performance time for discrimination of the two different hues. Similarly, with H_1B_1 and H_1B_2 (or H_2B_1 and H_2B_2) the baseline performance classification of brightness can be obtained. The third classification is to put two patches, H_1B_1 and H_1B_2 in one category (H_1), and H_2B_1 and H_2B_2 in another (H_2). If hue and brightness are integral dimensions, subjects cannot ignore, or filter out, irrelevant variation in brightness. That is, selective attention to hue alone should not be possible and consequently classification time should be slower than in the baseline conditions, since subjects now process 4 color patches rather than simply

2 values of hue. This difference between baseline and "filtering" conditions has been named filtering interference. On the other hand, if features are separable, the variation of brightness can be ignored, making the task effectively the same as the baseline. Therefore, for separable dimensions the filtering task speed should be equal to the baseline performance.

Conversely, if two cards are different not only in brightness but in hue also, like H_1B_1 versus H_2B_2, the overall magnitude of the difference between the two colors is bigger than when the colors differ in either dimension alone. Thus, when attention is not focused on a single dimension, the redundancy provided by the added dimensional distinction should facilitate performance, leading to faster sorting time (redundancy gain).

With this methodology, Garner and Felfoldy found that hue and brightness of color are integral dimensions; they produced both filtering interference and redundancy gain. However, the size of a circle and orientation of a radial line within the circle produced neither redundancy gains nor filtering interference, indicating that those dimensions are separable. Size and brightness, as well as color and shape were also separable dimensions (Gottwald & Garner, 1972).

This basic paradigm however has gradually shifted from a clear dichotomy of separable/integral dimensions to a continuum, two ends of which are integral and separable. Studies of dimensional structure seem to have been focusing its effort primarily on the relationship between development and a change in integral-separable processing mode (Shepp, 1989; Smith & Evans, 1989; Smith & Kemler-Nelson, 1984; Ward, 1980; Ward, 1983). Thus, the works in the field have not been directly related to issues of how component features are integrated to their holistic percept.

However, recently Melara and his colleagues (Melara, 1989; Melara & Day, 1992; Melara & Marks, 1990a; Melara & Marks, 1990b; Melara & Marks, 1990c; Melara & Marks, 1990d) developed a model that offers a new interpretation of these dimensionality data. In this model there are two modes of processing, focusing on attribute and stimulus level information. The attribute level is where information of features is accessed, and the stimulus level is where extracted attributes are "glued" together. However, these two modes are not processing stages that operate in the order of features to conjunctions as in more traditional feature analysis models. Instead, perceivers always have immediate and mandatory access to a set of primary reference axes which correspond to those dimensions that perceivers regard as "real" psychologically. All perceivers align the axes at one specific orientation in multidimensional stimulus space and extract individual attributes on those psychologically meaningful dimensions. For separable dimensions, attribute level processing is all that operates and subjects do not experience filtering interference in the classification tasks described earlier.

What are considered as integral dimensions in Garner's paradigm are those dimensions where subjects engage in the stimulus-level processing in Melara's model. Unlike a dimensionless whole or a blob (Lockhead, 1972), in an integral stimulus the attributes are still accessible in the stimulus-level processing mode. These attributes are not the same as ones that are extracted at the attribute-level, though, because they can be influenced or weighted by the context of other features and their perceptual meaning can be changed.

Within Melara's framework, subjects experience filtering interference because stimulus attributes take on these different perceptual meanings in integral dimensions and not because subjects try to "unglue" the relevant feature from the whole. For example, the same high pitch will have one perceptual meaning when paired with a "loud" attribute but a different meaning when paired with a "soft" attribute (Melara & Marks, 1990b). The loudness context acts to give differential weights in the extraction of pitch information. Therefore, in Melara's model, the difference between separable and integral dimensions is not in the separate and blended features, but in whether the component features themselves affect one another.

The idea of variation in "perceptual meaning," if it is extended to the visual processing discussed so far, is not entirely compatible with the notion of features in feature models like Treisman's (Treisman & Gelade, 1980; Treisman & Gormican, 1988). The unconditional, uniform treatment of all features as isolated and independent basic entities is the focus of the thesis.

Research Questions and Rationale

All three models of visual search do not deviate from the basic architecture of the feature-conjunction dichotomy. An entity is either a feature or a collection of features, and there is no change in the nature of features due to the context in which they are perceived. Nevertheless, research in separable/integral dimensions argues that different features of a visual object can be interrelated in different ways (Garner, 1974). There also is evidence that dimensions can be perceived differently while maintaining their featural identity (Melara & Marks, 1990b). If the same features can take on different perceptual meanings in different contexts as in Melara's model, the same features in highly familiar stimuli may be perceived differently compared to when they are in unfamiliar contexts. For instance, a line in a letter stimulus, an instance of familiar context, may be the same feature in Treisman's sense as the line in a non-letter stimulus, an instance of unfamiliar context. But when it is extracted by a line detector, would it be processed in the same manner regardless of the context in which it is embedded? Can the visual system, when it breaks down a letter stimulus into parts, extract a line in exactly the same way from highly familiar and highly unfamiliar wholes?

Treisman's model and her findings (Treisman & Gormican, 1988) offer an opportunity to look into the dynamics of single feature maps and to address those questions. The experimental question examined in this thesis is whether the workings of a single feature map, as they are manifested in Treisman's original line experiments (Treisman & Gormican, 1988), would remain the same in contexts of different familiarity. If the experimental stimuli are constructed in such a way that the attribute to define the target is exactly the same as that of the line experiments, then the resultant search data patterns would help to discern whether the line maps are affected by other features. If context does not affect a single feature map's activity, the observations made in the line experiments should appear unchanged in familiar and unfamiliar stimuli since the configuration of the line search task is preserved. If context does affect individual feature maps' activation, then there would be different search patterns depending on familiarity of the conjunction of features.

To determine whether the line map's activation is affected by familiarity, the lines in Treisman's experiments (Treisman & Gormican, 1988) were modified to four letters and non-letters leaving all other aspects of the experiments unaltered. A loop was added to all the lines in the long and the short target conditions. For letter arrays, the loop was added to the right side of the line to make the items "b" letters; for non-letter arrays, it was added to the left side to make the items "non-b"s (see Figure 3). The target was defined as it was in Treisman's experiments (the taller line in the long target condition, the shorter line in the short target condition), except that the loop was added on top of the target line making it a letter "p" in letter arrays and "non-p" in non-letter arrays (see Figure 3). Most importantly, the negative trials in both arrays also had "p" and "non-p"; one of the distractor lines was picked at random and made into "p" in the letter arrays and "non-p" in the non-letter arrays.

Since the same feature was added to all the items, nothing was changed within the configurations of individual feature maps, or in degree of similarity between conjunctions of the two features, line and loop. Similarity between target-distractor and distractor-

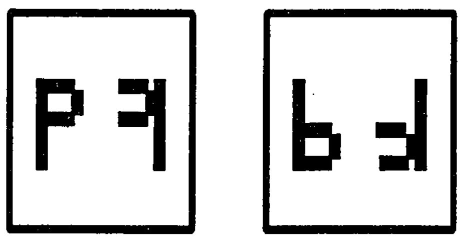

Figure 3. "p" and its non-letter version, "non-p"; "b" and its non-letter version, "non-b".

distractor should be the same as that in the configuration of lines only, and so should be the signal/noise ratio. The size of the difference between the target-present and target-absent arrays dictated by Weber's law should be the same as before this extra feature is added; there is no change for the line feature map before and after the loop feature's addition; there is no difference for the loop feature between the target-present and the target-absent trials. Therefore, all the variables that could affect the response speed in different search models remained unchanged, other than the spatial arrangements that make one configuration familiar letters and the other unfamiliar shapes.

Consequently any difference manifested between the letter and the non-letter arrays should be an effect of familiarity. If individual feature maps could be affected by familiarity, in the unfamiliar context the lines might maintain their activation levels separately from the loop features (see Figure 4). In this case, the expenditure of system resources that is utilized to process the added features should be the same for all search conditions. Hence, the non-letter arrays will generate a uniform increase of performance over that of the line arrays, because if the features could be treated as separate and independent from the lines, the processing cost for the loop features will add the constant amount of reaction time across all conditions. Whereas the absolute search time and its rate should increase due to the processings of extra features, the search data pattern should not change from that of the line experiments, since the output of the line feature maps would remain the same in both the target-present (positive) and the target-absent (negative) conditions.

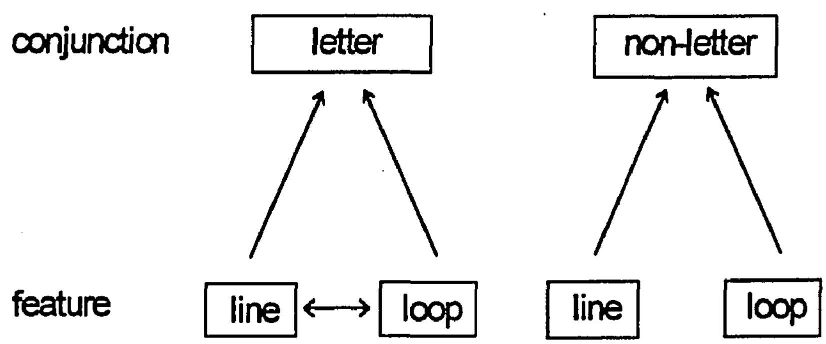

Figure 4. Suggested feature level difference in familiar and unfamiliar context. Upward arrows represent that features are grouped to form conjunctions. The horizontal arrow represents a presence of interaction between features in familiar context.

In a familiar context, the line features might not be entirely independent from the loop features. Their activation levels could be affected by the presence of the loop features. Exactly how and in what manner the line activation could be affected can not be predicted since mechanisms of inter-feature map interactions, if they exist, are not studied in the theoretical framework on which this thesis is based. The purpose of the current experiments simply is to find out if the features are independent as hitherto assumed.

The one logical consequence of the affected line feature map in familiar context would be that the target search of letter arrays should be a different kind of search from that of non-letter arrays. Although knowledge of precise mechanisms of the line map's activation in familiar contexts is not available, such an assumption of non-independence allows a prediction of the following kind.

If the line in "p" has a different perceptual meaning from the line in "b," then the search task in letter arrays will essentially become a two-target search task. Even though a "p" of different length is designated as the target (in experiments conducted), in fact, "p" exists in both the positive and the negative trials. In other words, there exists a line of different perceptual meaning from the lines of "b" in both positive and negative instances. The letter array search then would not deal with trials where all items are the same feature lines in negative trials and a single item is different from the rest in the positive trials. Rather, the search has to be of conditions where both positive and negative trials have one item that is different from the rest.

The difficulty of prediction of the search data in letter arrays is that there is no a priori reason to assume which of the two search instances, positive and negative, would be easier. On the surface, the detectability of the target would seem to depend on difference of line length because that still is the only difference in the configuration of stimuli. However, if the perceptual meanings of the line length itself is compromised by the presence of loops in the letter array, then the fact that the target line is different from the distractors is futile ground on which to base predictions of different levels of detectability.

Nevertheless, a prediction in relative terms is still possible. If the line in "p" is different from the line in "b" and the letter array search becomes something of a two-target search task, then even when the precise computation of the difference in the line feature map is unknown, the following predictions can be made. The search rate should not follow the usual 1 : 2 ratio of positive and negative trials because it is no longer a matter of finding the presence of a unique item. The slowest kind of search is when the search has to be exhaustive as in negative trials, since in order to know the target is absent all items should be examined. The letter array's negative trials, as defined by the same line length of all items, should not need the exhaustive search since they are no longer displays of all the same items. Therefore, the search rate of the positive and the negative trials in letter arrays could be similar to each other. For some reason, if "p" in one of the two instances (positive or negative) is much easier to detect than "p" in the other instance, then the search rates would not be similar. However, the difference should never be larger than that of positive and negative trials in non-letter arrays because the negative trials of non-letter arrays should always require exhaustive search.

The searches in non-letter arrays are assumed to be based on the line feature map's pooled activations, as they were in Treisman's line experiments. Lines in the non-letter arrays are not affected by loops; the loop feature's processing is something added to the line features' workings. Its increased expenditure of processing resource is coming from the fact that there is a second feature that needs to be processed as a part of a visual scene, even though its existence does not have direct bearing on the task of a target search.[13] As far as line maps are concerned, there thus should be no difference in target search tasks from Treisman's line experiments. Therefore, the search rate in non-letter arrays should be the ratio of 1 : 2 for positive and negative trials.

To examine these predictions, thirteen search tasks were conducted to investigate whether the processing of line features would be different in instances of familiar and unfamiliar stimuli. The first three experiments attempted to duplicate Treisman's line experiments and the next two experiments were conducted with only "p" and "non-p" items to establish base-line performance level. The remaining seven search tasks were "pb" and "non-pb" experiments utilizing different line lengths to examine whether the level of discriminability (the length differences between long and short lines) would affect

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[13] The loops are processed in letter arrays too. And they would be affected by line features differently from the loops in non-letter arrays. However, the configurations of the experiments do not allow the test of the change in the loop features; all search conditions are equivalent in terms of loop features.

the patterns of results. For instance, if discriminability is high enough to make the detection of the target item instantaneous, such level of salience of target attribute might override any difference in familiarity context.

Experiments

Throughout the description and discussion of the experiments, the term "short target" will refer to situations where target-present (positive) conditions are indicated by the presence of a single shorter line among 0, 5 or 11 longer lines; target-absent (negative) conditions are indicated by presence of 1, 6 and 12 longer lines. The term "long target" will refer to situations where positive conditions have one longer line among 0, 5 or 11 shorter lines, and negative conditions will have 1, 6 or 12 shorter lines.

Experiments 1, 2 and 3 replicated Treisman's line experiment (Treisman & Gormican, 1988). Experiments 4 and 5 used a single letter, "p," and its non-letter configuration (see Figure 3) for base line performances. Experiments 6 and 7 used two letters, "p" and "b," and their non-letter configurations (see Figure 3). Experiments 8 to 13 were replications of Experiments 6 and 7 with larger line length differences.

All experiments used the same general format, described below. Only the stimuli, instructions describing the specific stimuli, and the specific samples of subjects were changed across experiments.

General Method

Design. Each experiment employed 2 target conditions, 2 trial conditions, and 3 array sizes. The target conditions were short and long; the trial conditions were target-present (positive) and target-absent (negative); the array sizes were 1, 6 and 12 items. A completely within-subject design was always used, with all subjects responding in all al conditions.

Each subject (eight in each experiment) was tested on 6 blocks of trials, 3 blocks per each target condition. One half of the subjects received the long target condition first and the other half the short target condition first. Within each block, there was an equal number of trials for each array size, one half of them positive, the other half negative. The first of each series of 3 blocks was a practice block of 24 trials that were not included in the data analyses. Each of the remaining two blocks contained 42 trials, of which the first 6 were additional practice trials and not included in the analyses. Therefore, for each subject, data for analyses were based on 144 trials divided into 36 trials of 4 blocks; each cell in the analysis design (2 array sizes by 2 trial conditions by 2 target conditions) was based on 12 trials per subject, a total of 96 trials (from all 8 subjects). Within each block, all trial presentations were randomly ordered with the constraint that there should be no more than 5 consecutive same (yes or no) answers in a row.

Apparatus. The stimuli were presented on an Amiga 1084S monitor screen (25 cm high by 27.5 cm across) with a resolution of 320 by 200 pixels. One pixel was a dot of approximately 1 mm wide and high. Presentations of stimuli and the data collection were controlled with an Amiga 500 computer. A response pad with two telegraph keys (Lafayette Instruments) mounted 27 cm apart was connected to the Amiga 500 through its joystick port.

Stimuli. The viewing area was an 8.5 cm by 8.7 cm rectangle (112 by 93 pixels) at the center of the Amiga monitor. In order to determine stimulus item placement, a template (see Figure 5) was drawn that has 42 rectangles with sizes of 7 by 10 mm (nine by ten pixels). These 42 cells formed a roughly circular area. The intercell distance was three pixels and the farthest cell was 42 pixels away from the center of the viewing area and seven pixels from the surrounding square of one pixel width. All items were presented at locations that were randomly chosen from the 42 cells. They were viewed as illuminated in white on a dark gray background (the unilluminated monitor screen). During testing, only the large white empty square that marks the viewing area and the stimuli were visible; the cells illustrated in Figure 5 were never presented. The result was an impression of randomly dispersed items. The viewing distance during testing was about 90 cm.

Software and statistical package. A customized program was written in Aztec C for Amiga (Manx Software, 1989). The stimuli were drawn with Deluxe Paint IV for Amiga (Electronic Arts, 1991) and imported to the program for presentation. For experiments 1 to 7, all items were drawn in advance for each trial and the program presented them as a bitmap image. For the rest of the experiments, the 42 positions were fed into the program as coordinates (X,Y) and stimuli were drawn at the positions of the coordinates. At the end of each trial the program turned off the screen, and either copied a predrawn display set from a disk to the screen (for experiments 1 to 7) or drew each item at the randomly chosen locations (experiments 8 to 13). The program then turned

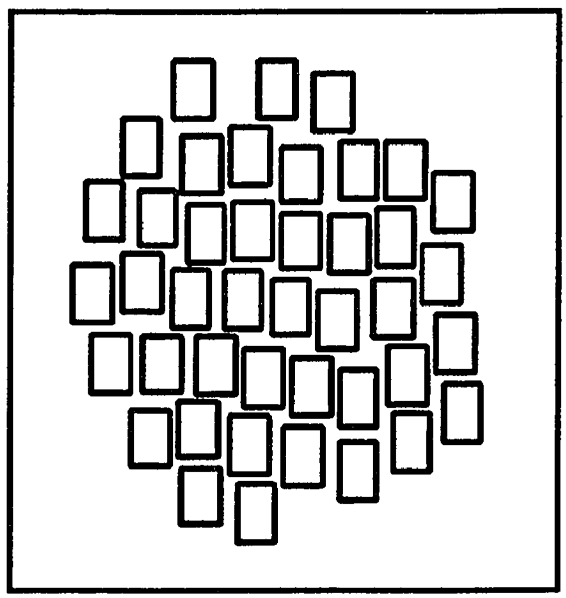

Figure 5. The template used for stimuli preparation.

the screen on again for the next trial when the raster scan reached the bottom of the screen. At the same time the screen was turned on, the Amiga 500's 8520 timer chip began to count its clock ticks and stopped when there was a response from the joystick port. The clock tick resolution was in microseconds and converted to ms unit by the program. When the response was made, the program turned off the screen, recorded the response and reaction time, then prepared the stimulus array for the next trial.

Procedure. Subjects were led to a quiet, dimly lit room and seated at a table in front of the computer monitor. Each target condition started with a set of example trials accompanied by a verbal instruction. Subjects were told about the difference between the target present and the target absent trials and to respond as soon as possible without making too many errors. The example trials included instances from every array size and every condition, and were the same as experimental trials except that each trial was initiated by an experimenter. The trials continued until subjects clearly understood the task and did not make any errors. The practice block was then presented, followed by two blocks of experimental trials. There was a brief break between blocks and a longer break between the target conditions.

At the beginning of each trial, with their index fingers resting gently on the response keys subjects saw a white cross in the center of a white empty square that was itself in the center of the screen. Five hundred ms later the stimulus array appeared, accompanied by an audible beep, and remained on until either a response key was pressed or three seconds elapsed. When a response was made, the screen went blank with a feedback beep, high for errors and low for correct responses. One second later the cross and the square appeared again for the next trial. The entire experiment lasted about 30 minutes.

Analyses

For all analyses, the statistical package, Statistica (1994) was used. For each experiment, multivariate analysis of variance for repeated measures was run on the mean reaction time for all correct trials. There was no attempt to exclude any outliers. A 2 by 2 by 3 within-subject factorial design was used: 2 target conditions (long and short), 2 trial conditions (positive and negative), and 3 array sizes (1, 6, 12).

For each subject, simple regression lines were fit to the target-present and target absent RT data of the 3 array sizes. The estimated slopes of these lines were submitted to analyses of planned comparisons using a linear contrast (-1, 0, 1) for array sizes.

For each mean slope for each condition, sums of squares for the array size and for its linear component were computed separately; the ratios of SS for the linear components over SS for the array size (the percentage of variation in the sample due to the linear components) were obtained and are reported in the Appendix B.

Error rates in each cell (in $2 \times 2 \times 3$ design) were computed as percentages of the total number of errors that 8 subjects made over the total number of trials for the condition (96 trials). They were reported as descriptive statistics.

All details of analyses for the final results and subject characteristics are reported in the Appendix B.

Experiments 1 and 2 (pixel 8 : 6, 8 : 5)

Treisman's original line experiment (Treisman & Gormican, 1988) included two versions, requiring relatively easy and difficult discriminations, defined by the size of the difference between the short and the long lines. In the easy version, the long line was 8 mm and the short line 5 mm; in the difficult version, the long line was the same 8 mm but the short line was 6.5 mm.

When RT was related to array size in the easy condition, the positive slope was 7.6 ms and the negative slope was 15.5 ms for the long target. For the short target, the positive slope was 14.3 ms and the negative slope was 28.3 ms. Finding the short line among longer lines was clearly more difficult than finding the long line among the short ones.

When the discrimination was more difficult (8 mm versus 6.5 mm) the slopes became much steeper, but the asymmetry still was observed. For the long target, slope values were 30 ms for the positive and 65 ms for the negative slopes; for the short target, they were 40 ms for the positive and 81 ms for the negative slopes.

The purpose of experiment 1 and 2 was to replicate Treisman's work and to establish a baseline performance level for specific procedures used in the current experiments. Experiment 1 was the difficult version with a difference of two pixels and Experiment 2 was the easy one with a difference of three pixels.

Method

Subjects. Sixteen subjects (8 subjects for Experiment 1, another 8 subjects for Experiment 2) from Brooklyn College participated for a partial fulfillment of a course credit. All subjects had normal or corrected-to-normal vision. Experiment 1 was completed before Experiment 2 was begun. Nevertheless, the two experiments were separated by a period of only a few days, and since the setting, general procedure and subject population remained exactly the same, they can legitimately be analyzed as one experiment with two groups if the need arises.

Stimuli. For Experiment 1, the long line length was eight pixels long (approximately 8 mm) and one pixel wide (approximately 1 mm); the short line was six pixels (approximately 6 mm) long and one pixel wide. The CRT computer screen had a resolution of 320 by 200 pixels. The length difference between target and distractor lines therefore was two pixels (see Figure 6). The position of each array item was picked at random from the 42 locations across all 216 trials (including practice), and no configuration was repeated within the same subject throughout the experiment. The same randomized sets were used for all 8 subjects in each experiment, but their presentation order for each subject was randomized individually. Experiment 2 used five pixels for the short line and the same eight pixels for the long line.

Results

Table 1 shows a summary of the data for Experiment 1. Mean RTs for correct trials of each subject were analyzed in the 2 × 2 × 2 ANOVA design described earlier.

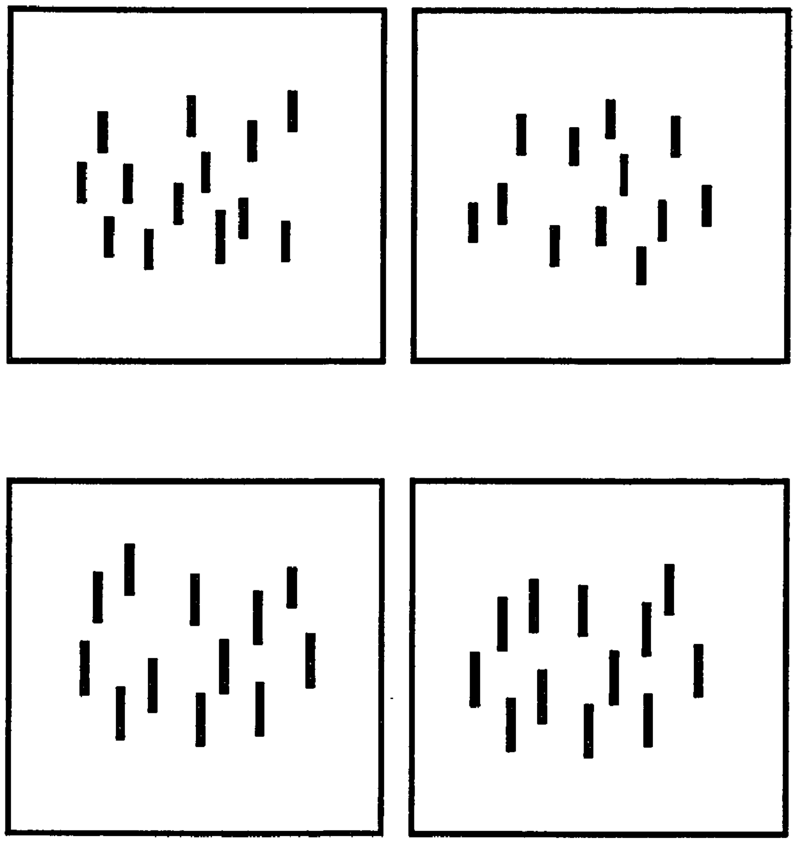

Figure 6. Examples of the long and the short target conditions for array size 12 in Experiment 1. The long and the short lines were eight and six pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

Table 1.

Mean RTs and slopes as a function of array size in Experiment 1.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	27.72	699.59	(2.1)	846.31	(4.2)	1005.01	(12.5)
Absent	39.73	757.31	(2.1)	1078.14	(3.1)	1201.58	(4.2)
				Short target			
Present	26.41	767.77	(1.0)	897.55	(5.2)	1058.14	(13.5)
Absent	76.98	754.17	(0.0)	1089.03	(3.1)	1597.99	(5.2)

Note. The values in parentheses represent error percentages. The stimuli were lines and the length difference was two pixels (8 pixels versus 6 pixels).

There was a significant three way interaction among target condition (long/short), trial condition (target present/absent), and array size (1, 6, 12) in Experiment 1 [$F(2,14) = 7.67, p < .01$]. Thus, the search rate relationship between the positive and the negative trials was different depending on whether the condition was the long or the short target search. The short target was searched at a slower rate than the long target condition (2 way interactions between target condition and array size, $F(2,14) = 14.23, p < 01$); and the slope for negative trials was steeper than that of the positive trials (2 way interactions between trial condition and array size, $F(2,14) = 9.91, p < .01$). There was no significant interaction between target condition and the trial condition [$F(1,7) = 1.48, p < .27$].

Overall, the negative trials were slower than the positive trials (main effect for trial condition, $F(1,7) = 19.17, p < .01$), and the bigger the array, the slower was the reaction time (array size main effect, $F(2,14) = 76.48, p < .01$). However, there was no main effect for target condition [$F(1,7) = 3.66, p < .10$]. Thus, if all the conditions were collapsed, the short target condition was not different from the long target condition.

Experiment 2 (see Table 2) showed the same patterns (see Appendix B tables for ANOVA results) except for the target main effect, which was significant [$F(1,7) = 7.15, p < .05$]. Particularly, the three way interaction was highly significant [$F(2,14) = 13.67, p < .01$] as it was in Experiment 1.

To examine the significant three way interactions, the positive and the negative trials were reanalyzed separately for the long and the short target conditions. Each analysis

Table 2.

Mean RTs and slopes as a function of array size in Experiment 2.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	9.52	595.81	(3.1)	654.07	(0.0)	701.15	(6.3)
Absent	12.96	678.06	(3.1)	745.22	(0.0)	820.73	(0.0)
				Short target			
Present	15.63	662.63	(2.1)	730.79	(2.1)	833.95	(5.2)
Absent	41.32	678.63	(1.0)	856.15	(3.1)	1131.41	(0.0)

Note. The values in parentheses represent error percentages. The stimuli were lines and the length difference was three pixels (8 pixels versus 5 pixels).

was conducted as a planned comparison to examine the linear interaction component (linear coefficients for array size -1, 0, 1). There was no significant difference between the slopes of the positive and the negative trials for the long target condition of Experiment 1 [$F(1,7) = 4.13, p < .09$]. The slope ratio of the positive to the negative trials was 1 : 1.4 (28 ms : 40 ms) for the long target condition. In contrast, the trial conditions in the short target condition were significantly different [$F(1,7) = 14.97, p < .01$]. The slope ratio of the positive to the negative trials was 1 : 3 (26 ms : 77 ms). As indicated in Table 2, to find the short target was not any more difficult than to find the long target. In fact, their slopes were almost the same (26 ms versus 28 ms). However, to decide that the target was absent was much more difficult in the short target condition than it was in the long target condition (77 ms versus 40 ms).

In Experiment 2, planned comparisons revealed that the positive and the negative trials were again not significantly different for the long target [$F(1,7) = 1.94, p < .21$], but the difference was significant in the short target condition [$F(1,7) = 31.11, p < .01$]. Also, finding the short target (slope = 15.63 ms) was more difficult than finding the long one (slope = 9.52 ms), although this asymmetry of the positive trials (between the long and the short target searches) was not significant (planned comparison, $F(1,7) = 2.79, p < .14$). On the other hand, this difference seems to have contributed to the significant trial main effect, which was absent in Experiment 1. The slope ratios of the positive to the negative trials were 1 : 1.36 (9.52 ms : 12.96 ms) and 1 : 2.64 (15.63 ms : 41.32 ms) for the long and the short target conditions, respectively.

Experiment 3 (pixel 9 : 5)

A difference of two pixels in line length is quite small. The activation levels of line distractors of eight pixels and six pixels may not have been different enough to affect subjects' performances. Experiment 2 therefore was repeated with a four pixel difference; the long and the short lines were nine pixels and five pixels long, respectively (see Figure 7). Subjects were eight students from an introductory psychology course in the College of Staten Island. For their participation, subjects received extra class credit and a payment of $3.00. All other aspects of the procedure remained the same as in Experiments 1 and 2.

Results

Results of Experiment 3 are summarized in Table 3. The three way interaction was not significant [$F(2,14) = 2.89, p < .09$], nor was the two way interaction between target condition and trial [$F(1,7) = 4.20, p < .08$]. Thus, the search time differences between the positive and negative trials over different array sizes were not different whether the target was long or short. The interactions between target and array size [$F(2,14) = 7.40$, $p < .01$], and trial and array size [$F(2,14) = 5.64, p < .02$] were significant. In other words, if the trial conditions are collapsed together, the search speed was faster in the long target than in the short target condition. With the two target conditions combined, the decision making for the target's absence was slower than finding the target as the array size became larger.

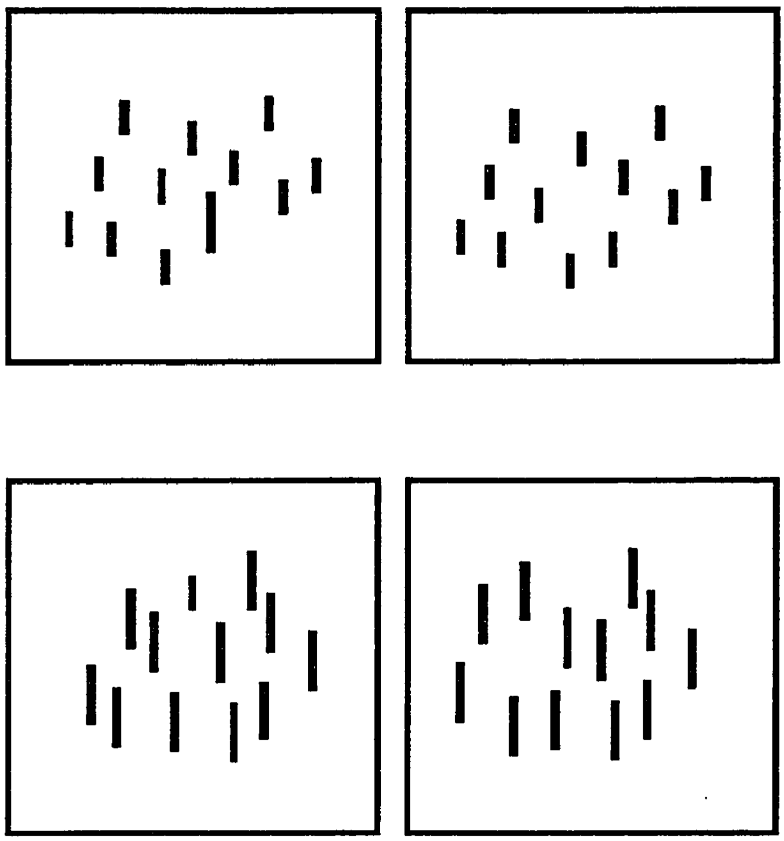

Figure 7. Examples of the long and the short target conditions for array size 12 in Experiment 3. The long and the short lines were nine and five pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

Table 3.

Mean RTs and slopes as a function of array size in Experiment 3.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	6.00	586.50	(1.0)	602.00	(1.0)	651.63	(4.2)
Absent	13.08	594.88	(2.1)	706.13	(1.0)	741.50	(0.0)
				Short target			
Present	12.48	576.63	(1.0)	644.50	(2.1)	714.25	(4.2)
Absent	27.38	633.75	(2.1)	737.88	(2.1)	933.00	(0.0)

Note. The values in parentheses represent error percentages. The stimuli were lines and the length difference was four pixels (9 pixels versus 4 pixels).

Overall, the negative trials were slower than the positive trials (the trial condition main effect, $F(1,7) = 28.41, p < .01$), and the bigger array sizes required longer search time (the array size main effect, $F(2,14) = 23.32, p < .01$). To find the short target was more difficult than to find the long target (the target condition main effect, $F(1,7) = 5.22, p < .06$).

To put it together, the results indicate that the short target condition was slower than the long target condition, but the negative trials were slower than the positive trials by the same magnitude in both target conditions. The overall ratio of the positive to the negative trials was 1 : 2. The linearity of the two way interaction between the trial condition (target present/absent) and array size was also significant in a planned comparison [$F(1,7) = 9.81, p < .05$].

Discussion

Figure 8 shows a graphic representation of the results of Experiments 1, 2 and 3. Overall, the short target conditions have larger slope values than the long target conditions, and the higher the discriminability the faster is reaction time, essentially replicating the asymmetry Treisman and Gormican (1988) found in their line experiments.

However, there are discrepancies between the current findings and those reported by Treisman and Gormican (1988). In their original experiments, the search rates for both the long and short target conditions generated 1 : 2 ratios. For the long target search, the

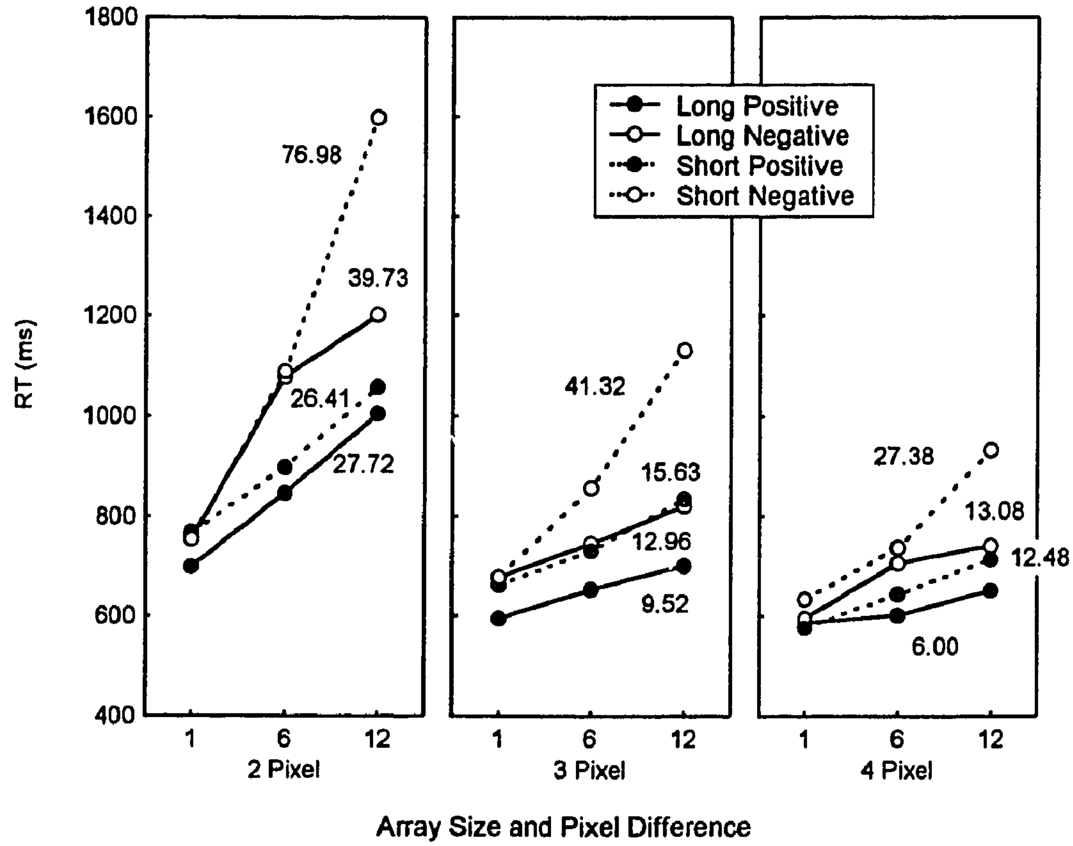

Figure 8. Mean RTs as a function of array sizes and target conditions for Experiments 1 (2 pixel), 2 (3 pixel), and 3 (4 pixel). The numbers on the graphs represent slope values.

slopes were 7.6 ms (positive) versus 15.5 ms (negative) for high discriminability displays (the difference of 5 mm and 8 mm), and 29.7 ms (positive) versus 64.7 ms (negative) for the low discriminability displays (the difference of 6.5 mm and 8 mm). The slopes for the short target conditions were 14.3 ms (positive) versus 28.3 ms (negative) for high discriminability displays and 40.0 ms (positive) versus 81.1 ms (negative) for low discriminability displays.

Whereas, the ratios (positive to negative) of the long target conditions in the current experiments changed from 1 : 1.40 (Experiment 1) to 1 : 1.36 (Experiment 2) to 1 : 2.08 (Experiment 3) as the discrimination became easier (from two pixel, three pixel and four pixel differences in line lengths as illustrated in Figure 9). The ratios for the short target conditions changed from 1 : 2.91 to 1 : 2.64 to 1 : 2.09 (see Figure 10). Thus, except for arrays of elements differing by four pixels, the ratios did not quite reach 1 : 2 in the long target conditions, and the negative trials were slow more than twice the positive trials in the short target conditions.

For the short target conditions, these very slow negative trials might indicate that subjects were double-checking judgments of the target's absence. The fact that the biggest ratio (1 : 2.91) was for the most difficult condition (two pixel difference) also corroborates this interpretation. When the target's length was only slightly shorter than the distractors, subjects might have doubly examined displays for some trials or some items in all trials. That tendency obviously was reduced as the discrimination became a bit easier (1 : 2.64 ratio in three pixel difference).

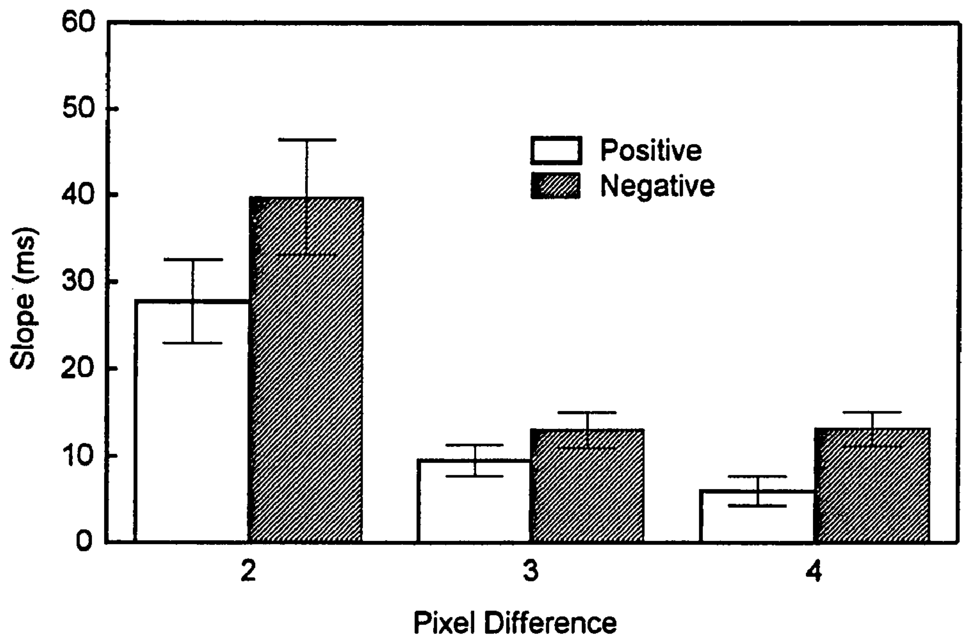

Figure 9. Comparisons of slopes (mean ± SE) of the positive and the negative trials for the long target conditions in Experiments 1 (pixel 2), 2 (pixel 3), and 3 (pixel 4).

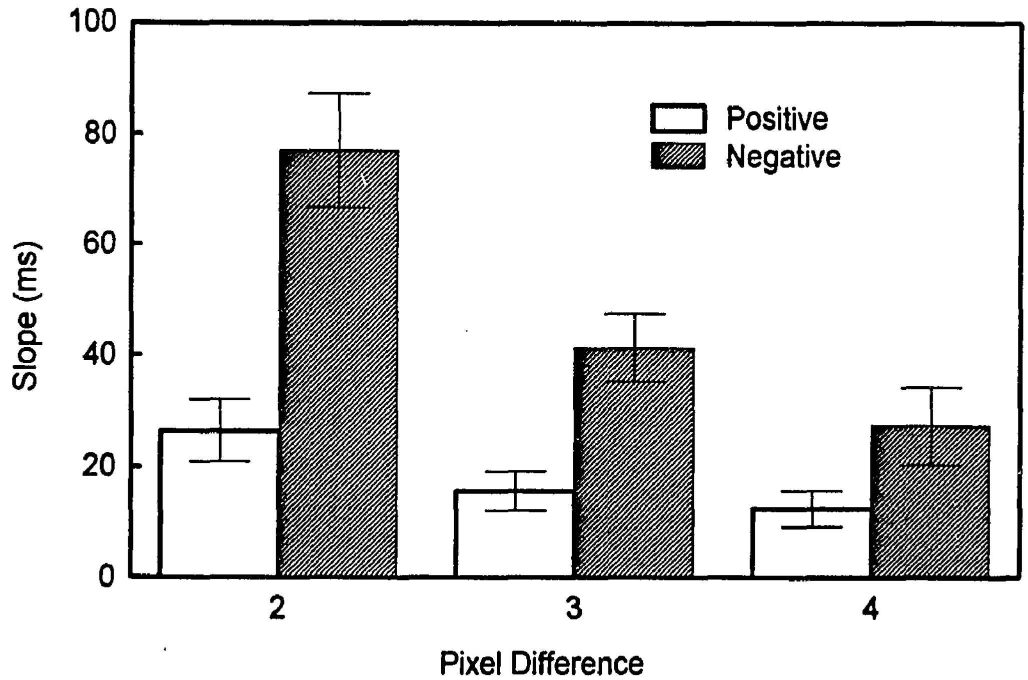

Figure 10. Comparisons of slopes (mean ± SE) of the positive and the negative trials for the short target conditions in Experiments 1 (pixel 2), 2 (pixel 3), and 3 (pixel 4).

However, such interpretations are not possible for the data in the long target conditions. Not only were the slope differences between positive and negative trials not significant, the ratio of 1 : 1.4 (for both two pixel and three pixel difference) is not close enough to 1 : 2 even at a descriptive level. Inspection of error rates does not explain the data either. For Experiment 1, although the error rates are higher in the positive trials of array size 12, most of the errors came from a single subject.[14] On the other hand, although the errors were low in Experiment 2, for the trials of array size 12 the positive trials showed higher error rates (6% in the positive, 0% in the negative trials) evenly distributed across subjects. Thus in Experiment 2 the error patterns indicate "premature termination of search" that could have rendered the search slopes small. However, it is not clear how to translate the inference to the difference between the slope values of the positive and the negative trials.[15]

The easiest condition (four pixel difference) was a very close replication of Treisman's easy condition. Although, overall RT was slower in Experiment 3 compared to Treisman and Gormican (1988),[16] slopes were remarkably similar. For the long target

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[14] With the subject's data excluded, the error rates of the long target condition, array size 12, were 5.2% for the positive and 4.1% for the negative trials.

[15] The true slope values, without the premature termination, would have been larger for both trial conditions than the data showed. But whether the larger slope values would render the difference between the positive and negative trials to 1 : 2 ratio is a difficult estimation.

[16] Differences between the mean intercept values were the following : 586 ms for the long target condition of Experiment 3; 499 ms for Treisman's long condition; 580 ms for the short condition of Experiment 3; 504 ms for Treisman's short condition.

conditions, the slopes were 6.00 ms (positive) versus 12.48 ms (negative) in Experiment 3 and 7.6 ms versus 15.5 ms in Treisman's; for the short target condition, they were 13.08 ms versus 27.38 ms in Experiment 3 and 14.3 ms versus 28.3 ms in Treisman's. Thus, to replicate Treisman's easy condition (the short line was 62.5% shorter than the long line; 5 mm versus 8 mm), a greater difference of line length was needed (the short line was 55.6% shorter than the long line; five pixels versus nine pixels) in the current experiment's configuration.

The implication of these results suggests that Experiment 1 might have required more difficult discriminations than the condition of low discriminability in Treisman's, although the proportional difference between the target and the distractor line lengths was larger in Experiment 1 than it was in Treisman's.[17] If the discrimination is very difficult, sub-grouping according to Weber's fraction would not be too useful since the

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[17] In Experiment 1, the difference was six pixels versus eight pixels (75%), in Experiment 2, it was five pixels versus eight pixels (62.5%), and in Treisman's difficult condition, it was 6.5 mm versus 8 mm (81.3%).

number of groups to form is too many.[18] That may have been the cause of the same positive slopes in the long and the short target conditions of Experiment 1.

However, such inferences still do not resolve the puzzling problem of the 1 : 1.4 ratio (positive to negative) in the long target conditions of Experiments 1 and 2. Moreover, based on search rates alone, Experiment 2 was not as difficult as Treisman's difficult condition. Therefore, this anomalous result cannot be entirely attributed to low discriminability. A conclusion of the three experiments should then be that except for a very high discriminability level, the search patterns are different when the target is longer compared to when it is shorter than the distractors. The underlying mechanisms of such differences are not known, and to be certain that the result is not an unspecified artifact, the experiments ought to be replicated in the future.[19]

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[18] To recapitulate, the disadvantage of the short target search resides in the fact that the activation difference (of the same magnitude as that of the long target condition) between the positive and the negative trials, when it was measured against the activation of the negative trials, is not the same as the difference in the long target condition. To make the difference equivalent to that of the long target condition, the short target search has to operate on the grouped items (rather than the entire array), and that is the reason for slow search speed. If the discrimination is so difficult that the number of subgroups to form in the long target condition itself is large, then the relative disadvantage of the short target search (due to the number of subgroups the search needs) will become negligible.

[19] For stimulus presentation in her line experiments, Treisman used a tachistoscope whereas the current experiment used a computer screen. Treisman does not report whether a chin rest was used (Treisman & Gormican, 1988). This type of procedural difference might have caused the discrepant results.

Experiments 4 and 5 (pixel 8 : 6)

In Treisman's model, the influences on processing of features that are common in both the target-present and the target-absent conditions are simply ignored. For example, empty circles (see Figure 2) become irrelevant because their activation level stays the same in both positive and negative trials. The model does not deal with the circle altogether. If this is an accurate description of the underlying processing, then the addition of an "irrelevant" feature to each array item should have little or no influence on performance. On the other hand, the features, although irrelevant, need to be processed since they are the part of the visual scene. If the irrelevant features have no effect on relevant features' activation, then their processing should not affect the output of relevant features. Therefore, with the addition of constant and irrelevant components to each array item the data pattern should not change from that of Experiment 1, although the absolute processing time could increase from that of the arrays with only lines.

If loops are attached on the left side of all the lines in both the long and the short target conditions (see non-letter version of Figure 3), then the task requires searching for a long "non-p" target among shorter "non-p" distractors and, analogously, a short "non-p" target among longer "non-p" distractors. In Treisman's pooled response model, there is no need to conjoin the lines and the loops to find the target because the only difference between the target "non-p" and the distractor "non-p" s is a difference in line lengths. Should that be the case, the task can still be accomplished by comparing pooled responses from the line feature map alone. Therefore, the search data patterns should be similar to those of Experiment 1. The negative trials should be twice as slow as the positive trials; the short target condition should be more difficult than the long target condition; and the overall RT should increase (compared to that of Experiment 1) because the loops have to be processed.

If the loops from the "non-p"s are displaced, without rotation, to the right sides of the vertical lines, the array items become familiar "p"s. The line maps in this configuration may not be completely independent from the loop maps as in the case of "non-p" arrays. There may exist an unknown kind of interaction between the line and the loop which is absent in the configuration of "non-p." The hypothesis is, as presented in the Research question and rationale section, that repeated exposures to this particular conjunction of the line and the loop, the "p," have now changed the perceptual meaning of the line. The line in "p" may no longer be the same as the line in "non-p" and the line map's activation and its output would now be different from the same map in "non-p" arrays.

The search task would still operate on the basis of line map's activation since lines are the only relevant features, however, since the task is to find a target within its own kind, no different search patterns are necessarily expected. The line feature map, when it operates on letter "p," is assumed to be activated in an unknown, yet different manner than when it operates on "non-p." But the line in the target "p" and the line in the distractor "p" are affected in the same way by the irrelevant loop features. Therefore, the amount or the kind of difference between the target and the distractors should be the same whether the search is conducted in "p" or "non-p" arrays. In that sense, the two searches are equivalent. In "non-p" arrays, the search would be conducted on the same line map as the line map in Experiment 1, in "p" arrays, it would be conducted on the affected (by the loop features) line map. But in both searches, the distinguishing characteristic of the target is the line length difference, and therefore, the data patterns should be similar.

Experiment 4 employed the "p" configuration (Figure 11) to determine how the added component of the loop, changing simple lines to familiar letters, affects performance. Experiment 5 was the "non-p" version (Figure 12) of Experiment 4. For both "p" and "non-p" arrays, whatever characterizes the target in one version equally applies to another. As far as elemental component features are concerned, the two versions used exactly the same set, although emergent relational features differ in the two situations.

If the loops have to be processed, even though their presence should neither help nor hurt performance according to Treisman's model, these experiments can be used to examine base line performance for processing of a constant amount of the same and irrelevant features.

Method

Subjects. Sixteen subjects from Brooklyn College, 8 subjects for Experiment 4 ("p" arrays) and 8 subjects for Experiment 5 ("non-p" arrays), participated for a partial fulfillment of a course credit. All subjects had normal or corrected-to-normal vision.

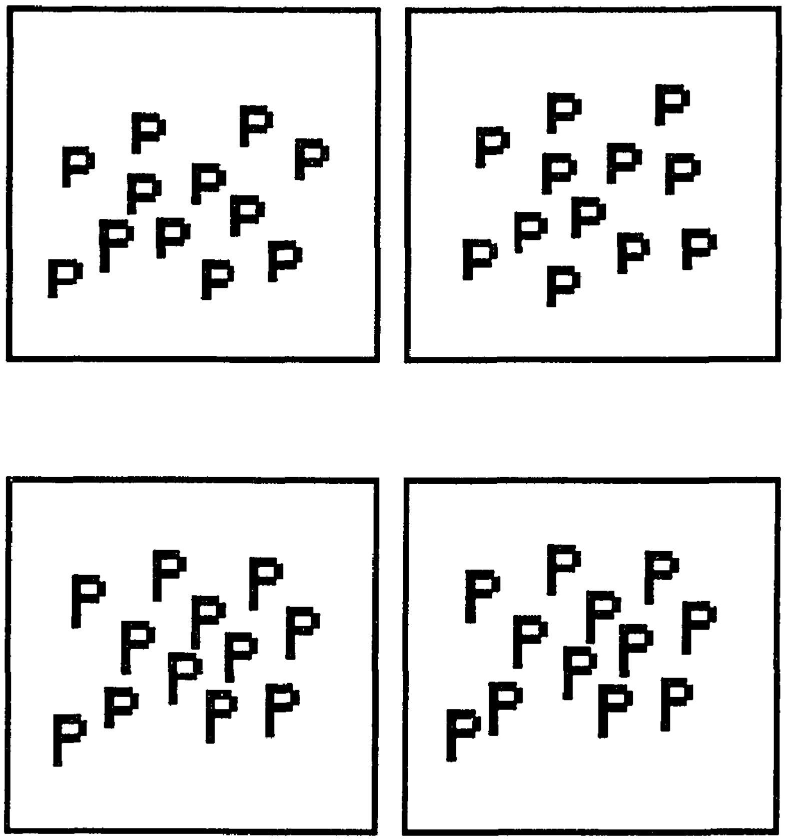

Figure 11. Examples of the long and the short target conditions for array size 12 in Experiment 4 (pp). The long and the short lines were eight and six pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

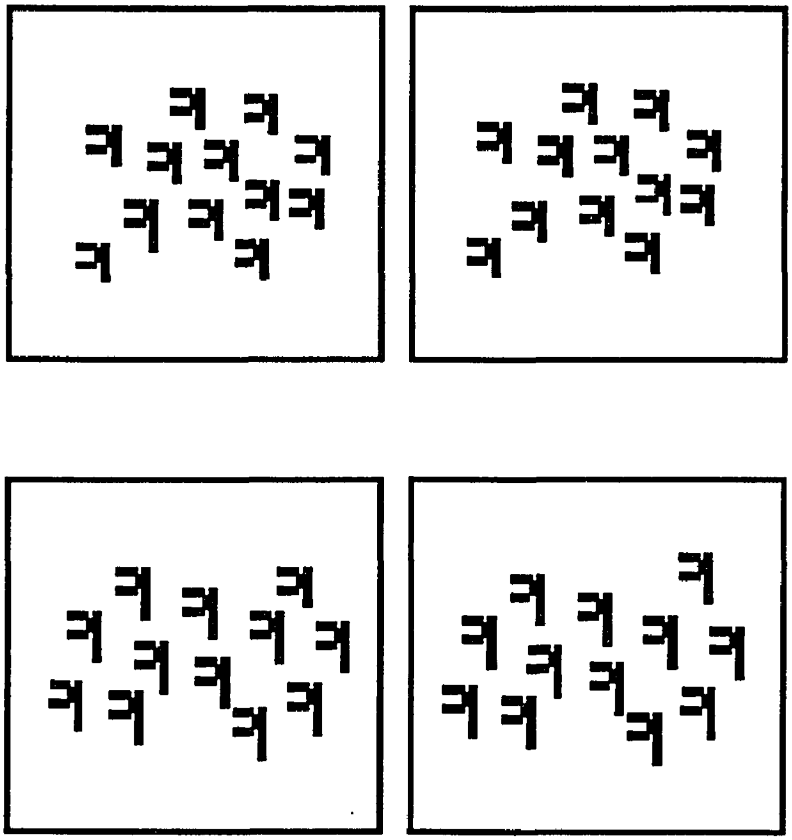

Figure12. Examples of the long and the short target conditions for array size 12 in Experiment 5 (non-pp). The long and the short lines were eight and six pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

Stimuli. Figure 11 provides illustration of the "p" stimuli for 12 item arrays, and Figure 12 illustrates the "non-p" stimuli. The long line length was eight pixels and the short line six pixels. The loops were three pixels (approximately 3 mm) on top and bottom and two pixels (approximately 2 mm) on the side. Positions of individual array items were randomly picked from the 42 potential locations for each trial in each condition in each block as described earlier.

Results

The search data for Experiment 4 are presented in Table 4. In the letter arrays, the search rate for negative trials was twice as slow as for the positive trials in the long target condition (1 : 2.01), and the ratio was slightly less than twice (1 : 1.82) in the short target condition. The difference was only marginally significant (three way interaction of target by trial by array, $F(2,14) = 3.98$, $p = .043$), and with the array size collapsed, there was no interaction between the target and the trial condition [$F(1,70) = 1.08$, $p < 34$]. As the array size got bigger, the negative trials were searched at a slower rate than the positive trials (two way interaction between trial and array size, $F(2,14) = 32.37$, $p < .01$) and the short target condition became more difficult than the long target condition (two way interaction between target and array size, $F(2,14) = 29.56$, $p < .01$). All main effects were highly significant; larger array sizes [$F(2,14) = 342.29$, $p < .01$], negative trials [$F(1,7) = 170.80$, $p < .01$], and short target conditions [$F(1,7) = 46.34$, $p < .01$] were more difficult than their comparison conditions.

Table 4.

Mean RTs and slopes as a function of array size in Experiment 4.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	32.75	628.42	(2.1)	843.30	(12.5)	991.65	(14.6)
Absent	66.09	703.30	(1.0)	1113.21	(0.0)	1434.92	(9.4)
				Short target			
Present	59.54	641.88	(1.0)	1101.79	(5.2)	1306.40	(19.8)
Absent	108.43	725.19	(1.0)	1379.65	(1.0)	1924.53	(8.3)

Note. The values in parentheses represent error percentages. The stimuli were letters (PP) and the length difference was two pixels (8 pixels versus 6 pixels).

The search results of the non-letter arrays (Table 5) were essentially the same as those of the letter arrays except for the nonsignificant three way interaction (see ANOVA tables in Appendix B). The slope ratio (positive to negative) was 1 : 2.68 in the long target, and 1 : 2.02 in the short target condition. Since the three way interaction was not significant, planned comparison was performed with equal weights for the two target conditions (1,1) contrasting trial condition (1, -1) and array sizes (-1, 0, 1) with target conditions collapsed together. The interaction was highly significant [$F(1,7) = 56.75, p < .01$]. The mean slopes for the positive trials and the negative trials were 42.77 ms and 94.29 ms, respectively, leading to the ratio of 1 : 2.2.

Thus, for both letter and non-letter arrays, the short target condition was more difficult than the long target condition over bigger array size and within each target condition, the average ratio of the positive to the negative trials was 1 : 2.

When the two experiments were reanalyzed together as two between subject groups, there was no group difference either as a main effect [$F(1,14) < 1$] or an interaction (group by target condition by array size) effect [$F(2,28) < 1$]. The patterns of results for letter and the non-letter groups were not different.

Discussion

There are three obvious points to be made regarding the results of Experiments 4 and 5 (see Figure 13). First, search asymmetry for longer versus shorter targets emerged with the two pixel difference employed in these arrays. Second, the ratio of search rates

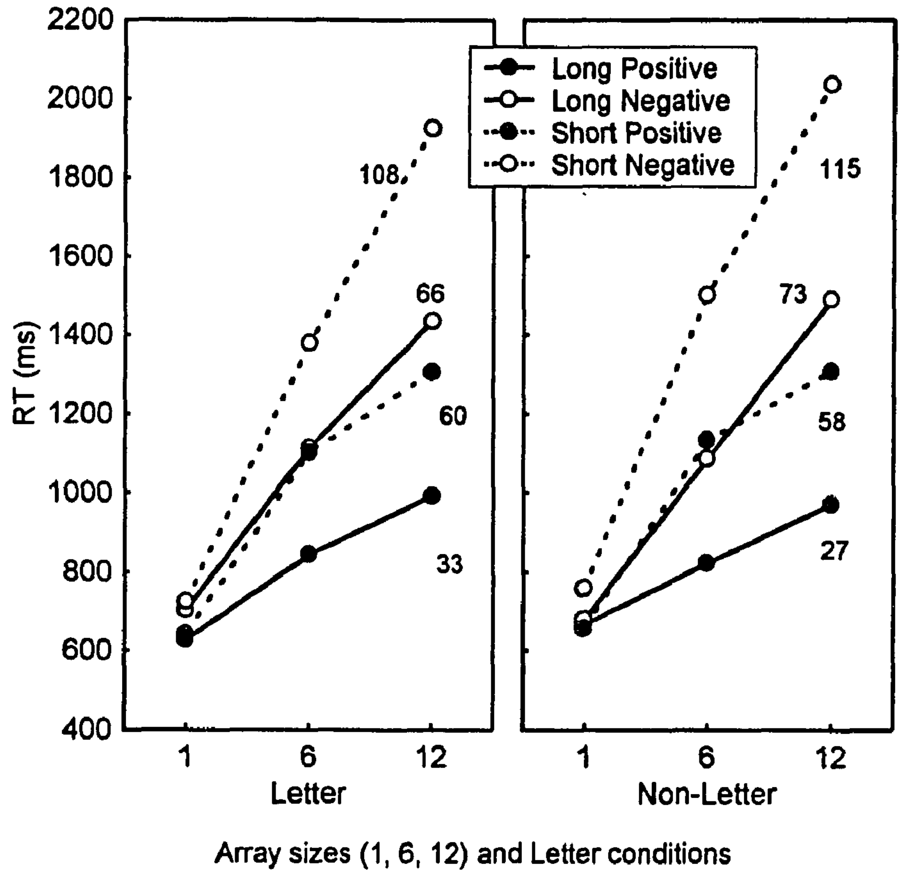

Figure 13. Mean RTs as a function of array sizes and target conditions in Experiment 4 (pp) and Experiment 5 (non-pp). The lines were eight and six pixels long. The numbers on the graphs represent slope values.

Table 5.

Mean RTs and slopes as a function of array size in Experiment 5.

		Array size					
Condition	Slope	1		6		12	
		Long target					
Present	27.42	667.77	(0.0)	822.76	(2.0)	970.45	(11.5)
Absent	73.43	680.38	(1.0)	1086.32	(0.0)	1490.41	(1.0)
		Short target					
Present	57.11	656.70	(0.0)	1132.37	(4.2)	1306.84	(9.4)
Absent	115.15	758.97	(0.0)	1503.16	(0.0)	2035.56	(11.5)

Note. The values in parentheses represent error percentages. The stimuli were non-letters (non-PP) and the length difference was two pixels (8 pixels versus 6 pixels).

for the positive to the negative trials for the long target conditions was 1 : 2 on average. Third, processing of letters and non-letters was not different.

The asymmetry of the positive trials was due to the very slow RT slopes for the short target positive conditions (26 ms for the line, 60 ms for the letter, 58 ms for the non-letter) while the long target positive responses remained comparable to that of Experiment 1 (27 ms for the line, 32 ms for the letter, 27 ms for the non-letter). It is as if the loops hid the short target. In viewing the stimulus arrays containing the items, the subjective impression was that the visual field looked crowded. Compared to the line stimulus, it seemed as if there simply were more of the things on the display. Although inter-item distance was constant, the same number of items as in the line conditions now occupied more space because of these added loops. However, this density effect alone can not explain the data pattern. If the density slowed down the search rate for the short targets, then it should have equally affected the long target conditions. The fact that the search rate for the long target essentially did not change from that of Experiment 1 indicates that density is not the major factor that has caused the asymmetry.

Although the positive trials for the long target condition did not change much from those of Experiment 1, the negative trials did; they were much slower than the positive trials and the ratio became 1 : 2 on average (compared to 1 : 1.4 in Experiment 1). It is not clear what made the negative trials (for the long target conditions of "p" and "non-p" array) twice as slow as the positive trials when the same kind of search for lines did not. There is a possibility that the current experiments induced the most typical conjunction search, in other words, that the search was based on the next higher level of stimulus configuration, where groupings of the features were accomplished. The plausibility of the argument is discussed later in the General Discussion section.

The search data for the short target condition were more or less as expected. The overall pattern indicated a slower search rate than for the line stimuli while maintaining a positive to negative slope relationship of 1 : 2.

Thus, the results of Experiments 4 and 5 indicate that the addition of irrelevant, constant features to the line array generates (a) the asymmetry of the long and the short target conditions, (b) within each condition, 1 : 2 search ratio, (c) overall increase in search rates.

Whether the addition of loops resulted in a conjunction that was novel or familiar did not seem to matter. Whatever it was that made the short target condition difficult, it operated similarly for letters and non-letters. The effect of loops upon the processing involved in the extraction of line features seems like one of the same magnitude and possibly of the same kind. However, even if a line in a letter has a different perceptual meaning from a line in a non-letter, in each condition, the same target letter "p" is compared with the same distractor letter "p"s with only the line length difference. In this situation, the critical comparison necessary for response selection does not differentiate featural nature in letters and non-letters. Therefore, even when the relevant feature, the line, is changed in its activation pattern, the processing system would not be expected to handle the addition of loop feature to line feature differentially in "p" and "non-p" arrays. The following experiments added a second letter.

Experiments 6 and 7 (pixel 8 : 6)

Examining the slope differences in Experiments 4 and 5 provided some clues as to whether the line features were affected by the presence of loops, yet it did not directly address the issue of whether the lines in familiar configurations could be qualitatively distinct from the lines of unfamiliar letter-like configurations. Even if the lines had different perceptual meanings in the context of "p" letters, it would not have been evident when subjects were asked to find "p" among "p"s since the equally affected line features are used to judge the difference between the target-present and the target-absent. Therefore, the results of Experiments 4 and 5 could not determine whether the data pattern would change due to the stimulus' familiarity over and beyond the mere presence of loops. To examine this question, a letter is needed that uses the same simple elements as "p," but is not "p." The letter "b" satisfies these conditions. "b" is like "p" in that it is composed of a vertical line and a closed loop. The only difference between "b" and "p" is that the loop position is shifted to the bottom of the vertical line (see Figure 14).

For the next set of experiments, the distractors were "b"s and "non-b"s. For example, in the long target condition, positive trials showed the target, a long "p," with distractors, short "b"s. Negative trials had short "b"s and one "p," but the "p" was as

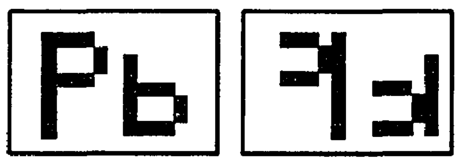

Figure 14. Configuration of stimuli used in Experiments 6 and 7. The left panel shows "p" and "b", and the right panel shows their non-letter version, "non-p" and "non-b".

short as "b"s. Therefore, there was a letter "p" in both positive and negative trials, but its length was longer/shorter in the positive trials and the same size as the "b" distractors in the negative trials (see Figure 15).

Because both target-present and target-absent trials included "p," finding the letter "p" alone would not lead to correct responses. Subjects still have to determine the length of the line feature within the "p." Unlike Experiment 4, where a particular perceptual meaning of a line feature was not related to the target, in this task features differentiating "p" from "b" can be utilized during the target search process.

If the presence of "b" creates other features that can differentiate "p" from "b," such as, a descender (the direction of a line in "p") versus an ascender (the direction of a line in "b"), or a closed top (in "p") versus a closed bottom loop (in "b"), the change is equally applicable to both target-present and target-absent trials, since both have "p" and "b." In other words, the single feature that differentiates positive trials from negative ones still is the line feature, just as it was in the previous experiments. However, the present experiment should reveal any change in the feature status of a line within the "p" context. Experiment 7 examined target search for a non-letter version of the "p" and "b," which used the same configuration as stimuli except for the side on which the loops were attached (see Figure 16).

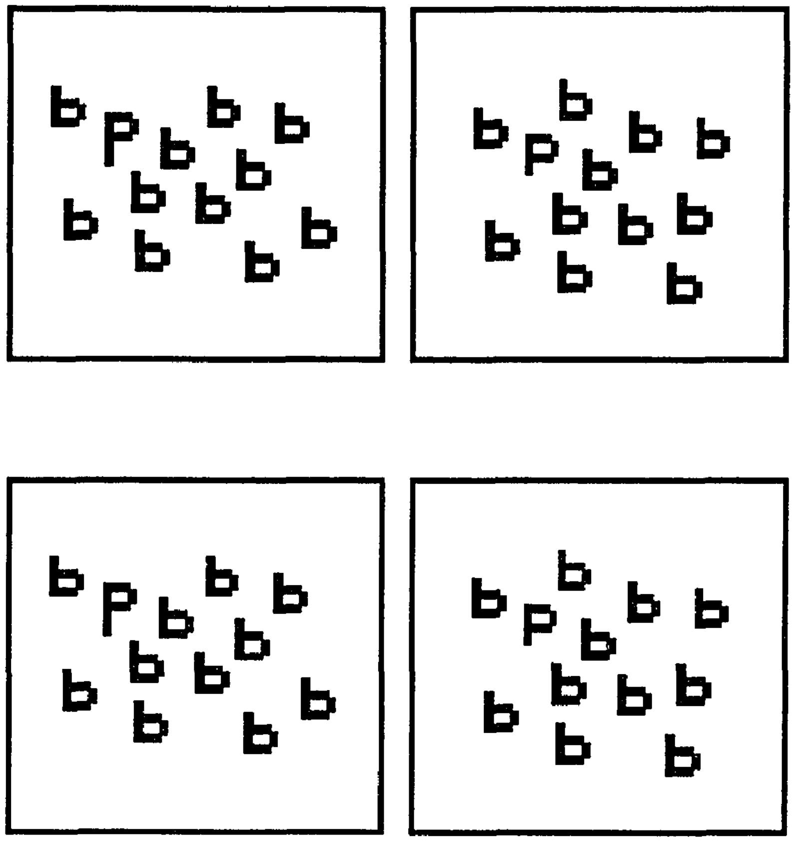

Figure 15. Examples of the long and the short target conditions for array size 12 in Experiment 6 (pb). The long and the short lines were eight and six pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

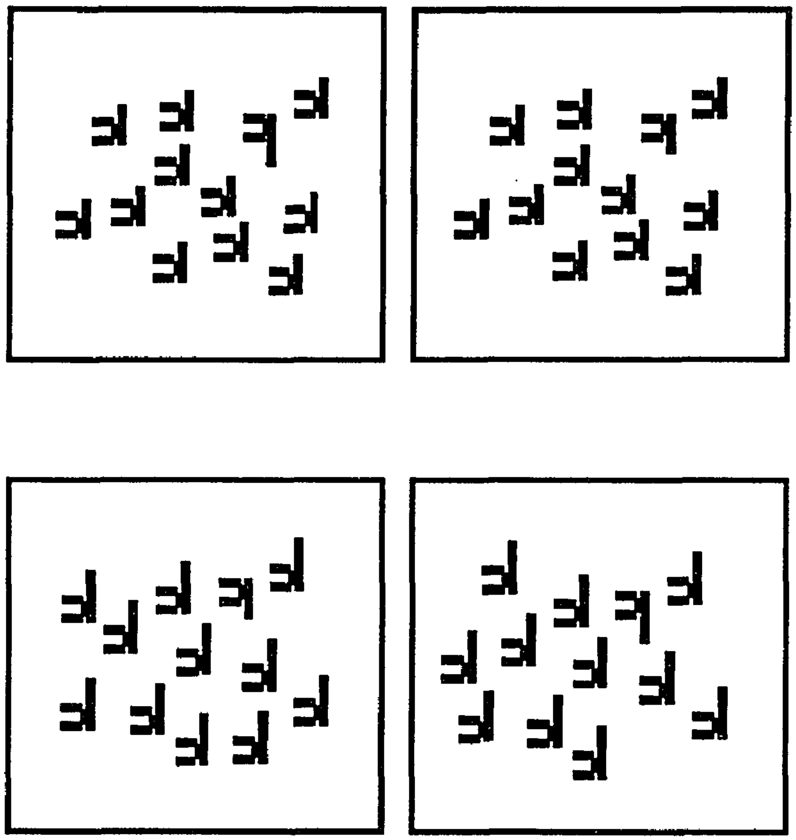

Figure 16. Examples of the long and the short target conditions for array size 12 in Experiment 7 (non-pb). The long and the short lines were eight and six pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version.

If a line feature in familiar context is affected by the presence of a loop feature at an early stage of visual processing, and as a consequence, a short line in "p," for example, becomes a perceptually different feature from a short line in "non-p," the search function will generate different patterns in letters and non-letters.

Method

Subjects. Sixteen subjects from Brooklyn College, 8 subjects for the letter version and 8 subjects for the non-letter version, participated for partial fulfillment of a course credit. All subjects had normal or corrected-to-normal vision. As before, the experiments were run separately over a period of a few days.

Stimuli. The method of preparation of the stimuli was as described for Experiments 4 and 5; the only difference was that the distractors were now "b"s. In negative trials, one "b" in the array was picked at random and converted to "p" (for array size of 1, the item in negative trials always was "p"). The difference between line lengths and the size of loops remained the same as in Experiments 4 and 5; eight pixels for the long and six pixel for the short line. As before, the item positions were randomly picked from the 42 potential locations for each trial in each condition in each block.

Results

For the letter arrays, the relationship between the positive and the negative trials was very different when the search was for the long target and for the short target condition (three way interaction, $F(2,14) = 6.88$, $p < .01$). In the long target condition, the slopes were 18.80 ms for the positive trials and 37.19 ms for the negative trials; in the short target condition, they were 50.75 ms for the positive trials and 39.14 ms for the negative trials (see Table 6). These differences were strong enough to show up in the two way interaction patterns. Thus if the target conditions were collapsed, there was no difference between the positive and the negative trials [$F(2,14) = 1.64$, $p < .23$]; with array size collapsed, the positive and the negative trials were different in the long and the short target conditions [$F(1,7) = 29.33$, $p < .01$]; as array size got bigger, the short target condition became progressively more difficult than the long target condition [$F(2,14) = 11.40$, $p < .01$].

Overall, the short target condition was more difficult than the long target condition [$F(1,7) = 23.91, p < .01$]; the bigger the array size was, the slower the reaction time was [$F(2,14) = 50.87, p < .01$]. There was no main effect of the trial condition [$F(1,7) = 3.3$, $p < .12$].

For the non-letter arrays of Experiment 7, the data pattern was quite different (note that one subject's data were lost due to a corrupted data disk). The slopes were 8.04 ms and 50.08 ms for the positive and the negative trials, respectively, in the long target condition. They were 54.35 ms and 89.66 ms in the short target condition (see Table 7). Thus, there is a huge difference between the positive and the negative trials for the long target condition compared to that of the short target condition. However, this difference between the target conditions was not significant [$F(2,12) < 1$].

Table 6.

Mean RTs and slopes as a function of array size in Experiment 6.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	18.80	575.71	(2.1)	702.60	(2.1)	784.44	(5.2)
Absent	37.19	628.54	(1.0)	813.70	(2.1)	1037.53	(1.0)
				Short target			
Present	50.75	617.43	(1.0)	967.53	(3.1)	1181.31	(10.4)
Absent	39.14	655.20	(3.1)	843.54	(1.0)	1085.26	(8.3)

Note. The values in parentheses represent error percentages. The stimuli were letters (pb) and the length difference was two pixels (8 pixels versus 6 pixels). The loops were large.

Table 7.

Mean RTs and slopes as a function of array size in Experiment 7.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	8.04	681.75	(1.2)	732.83	(0.0)	770.84	(6.0)
Absent	50.08	658.25	(2.4)	1015.96	(2.4)	1220.82	(1.2)
				Short target			
Present	54.35	641.07	(3.6)	1018.73	(6.0)	1245.19	(19.0)
Absent	89.66	752.10	(1.2)	1415.68	(6.0)	1751.04	(6.0)

Note. The values in parentheses represent error percentages. The stimuli were non-letters (non-pb) and the length difference was two pixels (8 pixels versus 6 pixels). The loops were large.

Ignoring the target conditions, the negative trials became progressively more difficult than the positive trials as the array size got bigger [$F(2,12) = 11.73, p < .01$]; ignoring the trial conditions, the short target condition got slower than the long target condition as the array size got bigger [$F(2,12) = 41.33, p < .01$]. On the other hand, with array size collapsed, there was no interaction between the target conditions and the trial conditions [$F(1,6) = 2.27, p < .20$]. All three main effects, target condition, trial condition and array size condition were highly significant [target condition, $F(1,6) = 24.29$ $p < .01$; trial condition, $F(1,6) = 15.48, p < .01$; and array sizes, $F(2,12) = 45.58$, $p < .01$]. To summarize, the short target was more difficult than the long target condition, the response speed for negative trials were slower than for the positive trials, and large array sizes required longer search time than the small arrays did.

The linear slope differences of both types of arrays were reexamined with planned comparison analyses. For the letter arrays, the difference between the positive and the negative trials was significant in the long target condition [$F(1,7) = 11.15, p < .02$], but was not in the short target condition [$F(1,7) = 3.01, p < .13$]. The slope ratio of the positive (18.80 ms) to the negative (37.19 ms) in the long target condition was 1 : 1.98, and 1 : 0.8 in the short target condition (50.75 ms : 39.14 ms).

Since the three way interaction was not significant in the non-letter array, the two way interaction of the trial condition by array sizes was analyzed with target condition combined. Contrasting the positive and the negative trial conditions (1, -1) over the array size (-1, 0, 1), with equal weights for the target condition (1, 1), the two way interaction's linear components also were significant [$F(1,6) = 12.95, p < .02$]. The ratio of the positive to the negative trials averaged over target conditions was 1 : 2.25 (31.12 ms for the positive trials, 69.97 ms for the negative trials).

Discussion

Like in Experiments 4 and 5, the current tasks show slow serial searches except for one condition (the positive slope in the long target of the non-letter arrays). Error rates are not low, particularly in the array size of 12 items. Overall the short target conditions were slower than the long target conditions.

Unlike in Experiments 4 and 5, performance for the letter arrays was different from the non-letter arrays in Experiments 6 and 7 (see Figure 17). Specifically, subjects responded differently toward negative trials in letters and non-letters. If the stimuli were letters, search slope for negative trials was not any slower than for the positive trials in the short target condition; for non-letters, slopes for negative trials were always slower than positive ones regardless of the target conditions (see Figure 18). Thus, the slope ratios were similar between the letter and non-letter arrays when searching for the long target (1 : 1.98 for the letter array, an average of 1 : 2.25 for the non-letter array). The ratios were very different for the short target conditions (1 : 0.8 for the letter arrays, and 1 : 2.25 for the non-letter arrays overall).

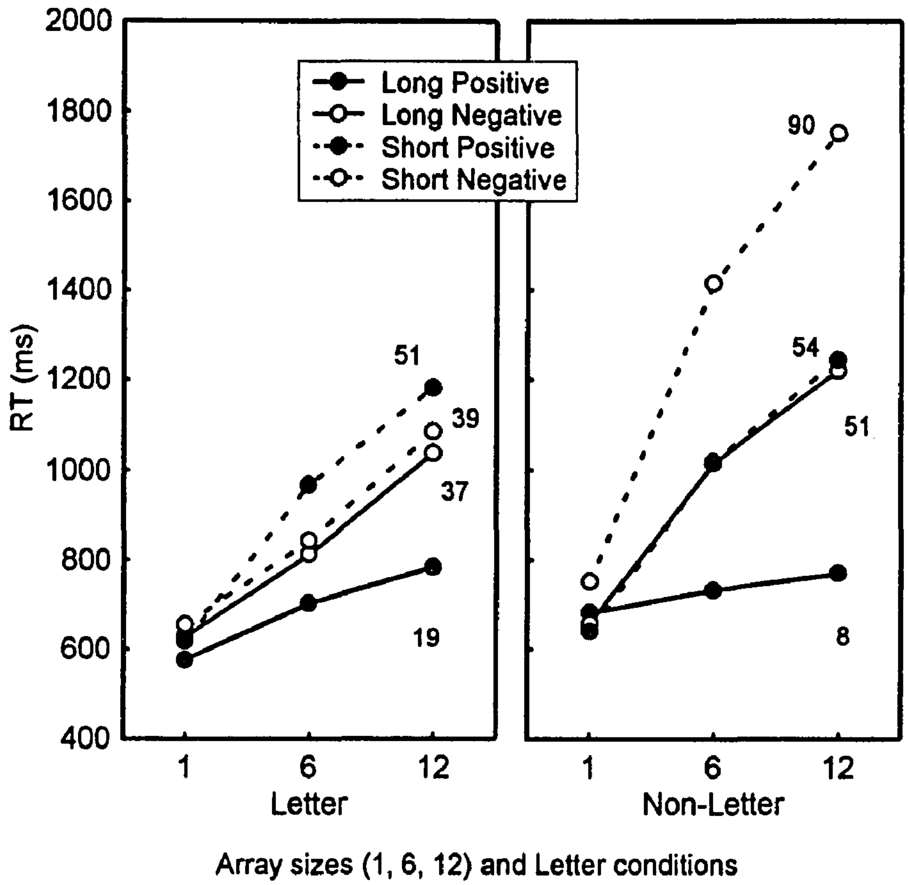

Figure 17. Mean RTs as a function of array sizes and target conditions in Experiment 6 (pb) and Experiment 7 (non-pb). The lines were eight and six pixels long. The numbers on the graphs represent slope values.

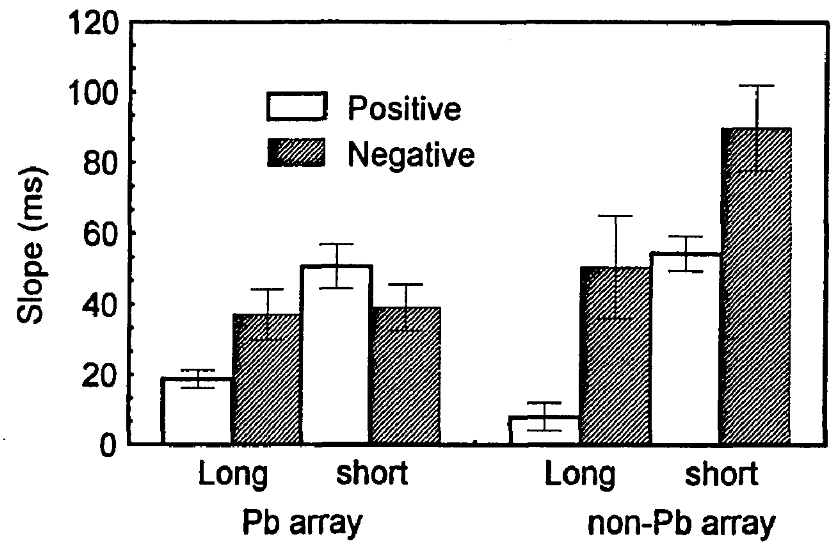

Figure 18. Comparisons of slopes (mean ± SE) of the positive and the negative trials for Experiments 6 (pb) and 7 (non-pb). The lines were eight and six pixels long.

However, the data pattern of the non-letter arrays was confusing in some respects. First, one subject's data had to be discarded in the non-letter group. Second, the positive trials in the short condition of the non-letter arrays showed a much higher error rate (9.5%) than that of the letter arrays (4.9%).[20] Thus, there is a possibility that subjects in the non-letter arrays might have responded fast at the expense of accuracy in that particular condition. Third, the positive trials in the long target conditions were unusually fast (slope = 8.04 ms) compared to other conditions (the range of 18.80 ms to 89.66 ms). Also, as discussed in Experiments 1 to 3, the level of discriminability at two pixel difference between targets and distractors in the current task might have been too difficult to yield unambiguous data results.

For these reasons, the data patterns of Experiments 6 and 7 were reexamined with a higher level of discriminability. Experiments 6 and 7 were replicated in Experiments 8 and 9, but the difference between target and distractor line features was increased to three pixels.

Experiments 8 and 9 (pixel 8 : 5)

Method

Stimuli. The long line length was the same eight pixels as used in Experiments 6 and 7. The short line was now five pixels in length (approximately 5 mm) instead of six pixels

[20] Had subjects in the non-letter arrays slowed down to the accuracy level of the letter arrays, the non-letter arrays might have also revealed similar slopes for the positive and the negative trials in the short target condition as subjects in the letter arrays did.

employed in the previous experiments. When the line was reduced to five pixels, the short "p" and the short "b" no longer resembled familiar letters because their stems were too short compared to the loop sizes. To rectify this problem, the loop size was reduced by one pixel. Specifically, the three pixels on the loops' top and bottom remained unchanged from previous stimuli, but the side was reduced to one pixel from two pixels (see Figure 19). All other aspects of the design and procedure remained the same as previously described.

Subjects. Sixteen subjects from Brooklyn College, 8 subjects for "pb" arrays and 8 subjects for "non-pb" arrays, participated for a partial fulfillment of a course credit. All subjects had normal or corrected-to-normal vision.

Results

Tables 8 and 9 show the summary of the letter array and the non-letter array data, respectively. For the letter group, although the slope ratios were 1 : 1.85 (10.79 ms : 19.95 ms) for the long target and 1 : 1.0 (55.12 ms : 55.67 ms) for the short target condition, the three way interaction was not significant [$F(2,14) < 1$]. Nor was the two way interaction between trial (positive/negative) and array size [$F(2,14) < 1$]. With trial conditions combined, the short target condition was searched at a slower rate than the long target condition as the array size increased [$F(1,7) = 25.44$, $p < .01$]. Overall, it took longer reaction time for the larger array size [$F(2,14) = 39.35$, $p < .01$]; the short target condition was more difficult than the long target condition [$F(1,7) = 28.38$, $p <$

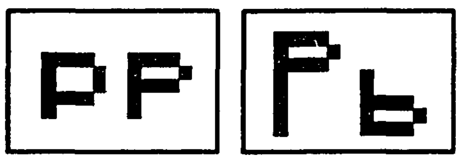

Figure 19. Configuration of stimuli used in Experiments 8. The left panel contrasts “p” of pixel size five that has a large loop with the same size “p” that has a small loop. The right panel shows “p” and “b” used in Experiment 8.

Table 8.

Mean RTs and slopes as a function of array size in Experiment 8.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	10.79	566.85	(1.0)	636.77	(2.1)	686.48	(12.5)
Absent	19.95	640.29	(5.2)	758.82	(3.1)	860.85	(1.0)
				Short target			
Present	55.12	608.24	(2.1)	865.35	(5.2)	1213.44	(10.4)
Absent	55.67	647.33	(4.2)	940.51	(2.1)	1260.56	(15.6)

Note. The values in parentheses represent error percentages. The stimuli were letters (pb) and the length difference was three pixels (8 pixels versus 5 pixels). The loops were small.

Table 9.

Mean RTs and slopes as a function of array size in Experiment 9.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	8.37	589.61	(1.0)	640.27	(2.1)	682.23	(3.1)
Absent	21.58	650.17	(1.0)	785.94	(0.0)	889.21	(1.0)
				Short target			
Present	32.12	640.94	(0.0)	941.64	(5.2)	1002.55	(14.6)
Absent	80.01	673.47	(1.0)	1227.94	(0.0)	1562.69	(2.1)

Note. The values in parentheses represent error percentages. The stimuli were non-letters (non-pb) and the length difference was three pixels (8 pixels versus 5 pixels). The loops were small.

.01]; but there was no difference between the positive and the negative trials [$F(1,7) = 3,38, p < .11$].

The results for the non-letter group was rather different from those of the letter group, The ratio of the positive to the negative trials was 1 : 2.58 (8.37 ms versus 21.58 ms) in the long target condition, and 1 : 2.49 (32.12 ms versus 80.01 ms) in the short target. The three way interaction was significant [$F(2,14) = 7.68, p < .01$].[21] In fact, all the two way interactions and the main effects were highly significant (see ANOVA tables in Appendix B).

The ANOVA interpretations were extended in planned comparison analyses also. For the letter arrays, the differences between the positive and the negative trials were not significant for either the long target [$F(1,7) = 3.75, p < .09$] or the short target conditions [$F(1,7) < 1$]. The differences in slopes were significant for search in the non-letter arrays though, for both the long [$F(1,7) = 7.67, p < .03$] and the short target conditions [$F(1,7) = 18.01, p < .01$].

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[21] The significant three way interaction means that the RT differences between the trial conditions at each array size were not the same between the long and the short target conditions. In other words, the three way interaction represents the significance of the absolute RT differences whereas the ratios indicate the relative (or proportional) differences between the slopes. Therefore, the three way interaction can be significant even when the slope ratios themselves are not different. Conversely, the absence of the three way interaction does not necessarily indicate that the two ratios of the long and the short target conditions are not different. This makes it necessary to examine the three way interaction in the context of individual slopes for each condition.

Thus, following the analyses' results, the letter arrays showed an overall slope of 15.37 for the long target and 55.40 ms for the short target conditions, with no significant difference between the positive and the negative trials in either target conditions. The slope ratios for the non-letter arrays were 1 : 2.58 for the long target condition and 1 : 2.49 for the short target condition.

Discussion

The non-letter group's data patterns (see Figure 20) were similar to the results of the previous Experiment 7. Although a three way interaction was not significant in the two pixel "non-pb" classification, and it was for the three pixel "non-pb" difference, the interaction did not reflect a difference in slope ratios, and therefore does not bear any direct importance to the purpose of current work. Thus, with the average slope ratio of 1 : 2.3 in the two pixel difference and 1 : 2.5 in the three pixel difference, it would be a valid conclusion that for the non-letter arrays, search rates for the negative trials were slower than the positive trials by a factor of slightly more than twice, regardless of the target conditions. Further, the short target condition was clearly more difficult than the long target condition (see Figure 21).

For the letter arrays, although the probability levels changed from significant (two pixel) to nonsignificant (three pixel) in the three way interactions, at a descriptive level the pattern of results remained similar. For the long target conditions, the slopes were

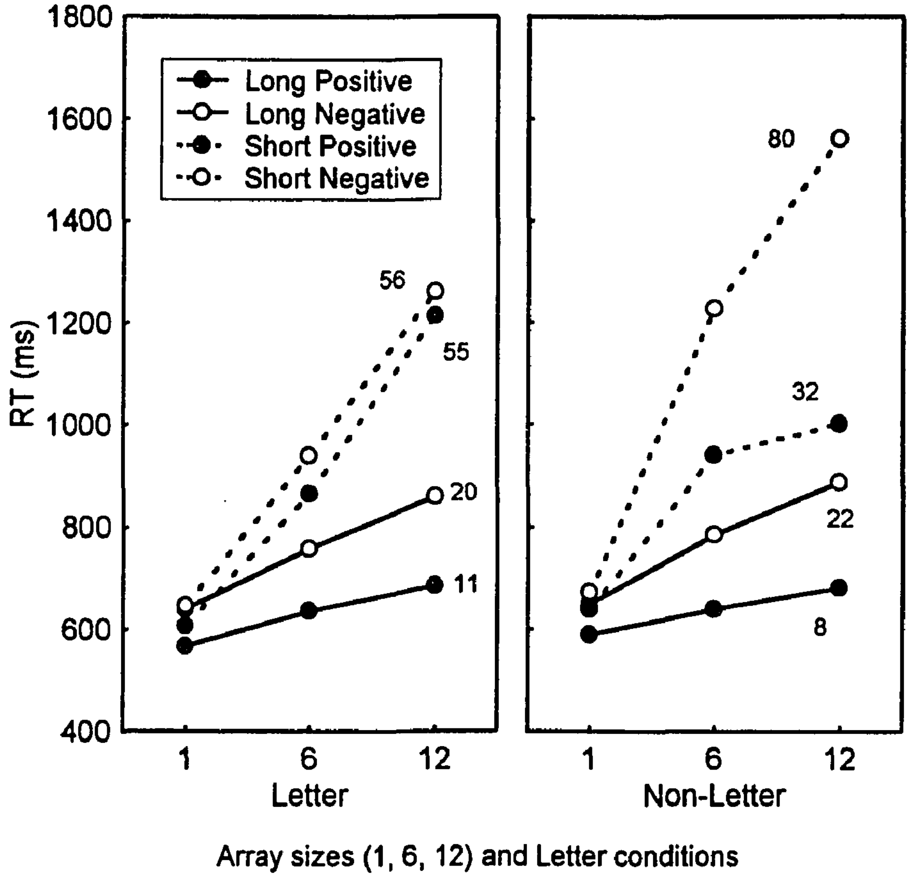

Figure 20. Mean RTs as a function of array sizes and target conditions in Experiment 8 (pb) and Experiment 9 (non-pb). The lines were eight and five pixels long. The loop sizes were small. The numbers on the graphs represent slope values.

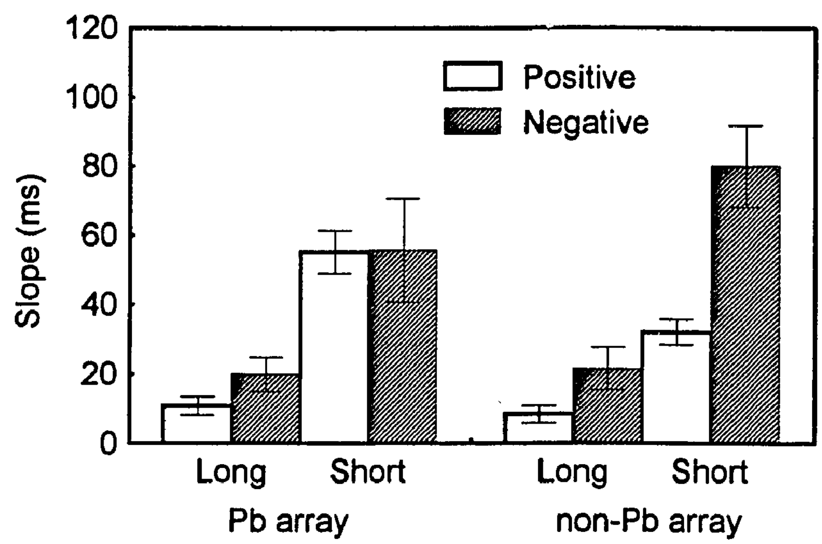

Figure 21. Comparisons of slopes (mean ± SE) of the positive and the negative trials for the long and the short target conditions in Experiments 8 and 9. The lines were eight and five pixels long. The loop sizes were small.

18.80 ms and 37.19 ms for the positive and the negative trials, respectively, at discriminability level of two pixels; they were 10.79 ms and 19.95 ms at discriminability level of three pixels. Thus, overall the stimuli containing three pixel differences were easier to search than stimuli differing by two pixels, as expected, but the slope ratios were almost equal (1 : 1.8 and 1 : 1.9). Interestingly, the patterns for the short target conditions were slightly different between the two levels of discriminability. For the two pixel difference, the negative trials (39.14 ms) were actually faster than the positive trials (50.75 ms) and with the three pixel difference they became almost identical (55.12 ms and 55.67 ms).

When the two letter arrays were analyzed as a single four way design (with the two letter arrays as two levels of a discriminability variable), the four way interaction (i.e., the data patterns between the two levels of discriminability) was not significant, but the three way interaction (between target, trial and array size) was.[22] This interaction indicates that RT differences between the positive and negative trials were not the same for the long and the short target conditions.

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[22] Analyses results of the letter arrays (two pixel and three pixel) : four way interaction [$F(2,28) = 1.28, p < .30$]; three way interaction [$F(2,28) = 3.43, p < .05$]; planned comparison of the positive and the negative trials in the long target with the two discriminability level collapsed together [$F(1,15) = 13.85, p < .003$]; planned comparison of the same ratio in the short target condition [$F(1,15) < 1$]. Mean slopes : 14.79 ms for the positive and 28.57 ms for the negative trials for the long target condition; 52.93 ms for the positive and 47.40 ms for the negative trials in the short target condition.

In conclusion then, with the same level of discriminability (three pixel), the same number of items in each array (1, 6 and 12), the same two features (line and loop), and the same difference between the target and the distractors (line length), subjects respond differently toward the "p" and the "non-p." If the configuration is of unfamiliar items, they seem to follow a typical serial self-terminating search procedure. That the negative trials took slightly more than twice as long as the positive trials might indicate that subjects were probably double checking some trials when the target was absent.

If the stimulus items were familiar letters, a clear difference between the long and the short target conditions emerged. The search speed, measured as slope values, and self-terminating method, inferred from the slope ratios of the positive to the negative trials, are not much different from the unfamiliar arrays[23] if the search goal is to find the item that contains a longer line than the distractors have. On the other hand, if the goal is to find the item with a shorter line, a more difficult condition in Treisman's framework, there does not seem to be a search speed difference between the positive and the negative trials. In fact, it appears that the negative trials could even be easier than the

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[23] In the light of the different patterns in the short target condition, there is no guarantee that the similar slopes and ratios in the long target conditions between familiar and unfamiliar arrays are the results of the same underlying mechanism.

positive ones. The large values of the slopes show that the search went on slowly in a serial manner, but there is certainly no indication of exhaustive search.[24]

Therefore, the hypothesis of the thesis, that the search speed in positive and negative trials should be similar to each other in familiar context, and if not, the difference should be less than that of unfamiliar context was confirmed, but only in the short target condition.

For these experiments, other than the line length, the size of the loop also was different from the two pixel versions. To find out whether the loop size had any effect, experiments of the two pixel difference were repeated with the smaller loops that were used in the current experiments. If the size of the loop caused the change in the current data, the pattern should remain the same in the next experiments, since both use the same size loops.

Experiments 10 and 11 (pixel 8 : 6)

Method

Stimuli. There were two modifications in Experiments 10 and 11 compared to Experiments 6 and 7 (two pixel difference with large loop). The first was that the loops were reduced by one pixel. The second was that the positions of the items on the display

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[24] For the two search slopes (of positive and negative trials) to be equal, both searches would have to be of the same kind, either self-terminating or exhaustive. The present hypothesis is that both searches are self-terminating for the reasons discussed in the Research question and rationale.

were different for every trial for every subject. In the earlier experiment, there were 144 different display configurations and the same set was used for all subjects in randomized orders. For the current experiments, there were 8 different sets of 144 different trials; no display was repeated. The long line length was eight pixels; the short line was six pixels; the loop was three pixels wide and three pixels long.

Subjects. Sixteen volunteers, recruited staff at the Institute of Basic Research, participated. The letter group was tested before the non-letter group. All had normal or corrected-to-normal vision.

Results

The slopes for the letter arrays were 11.19 ms and 19.21 ms for the positive and the negative trials, respectively, in the long target and 44.55 ms and 29.31 ms, respectively, in the short target condition (see Table 10). The ratios were 1 : 1.72 (long target) and 1 : 0.66 (short target). The three way interaction was significant [$F(2,14) = 7.11, p < .01$]. The two way interaction between trial condition and array size, with target condition collapsed, was not significant [$F(2,14) < 1$]. As in the earlier experiments, with negative and positive trials collapsed together the short target condition slowed much more than the long target condition as the array size increased [$F(2,14) = 34.69, p < .01$]. The two way interaction between the target condition and the trial condition was also significant [$F(1,7) = 38.54, p < .01$]. Thus, with array size collapsed, on average the negative trials were slower than the positive trials in the long target, but the difference was much smaller in the short target condition. The main effects of the target condition [$F(2,14) =$

Table 10.

Mean RTs and slopes as a function of array size in Experiment 10.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	11.19	618.10	(5.2)	724.29	(7.3)	744.11	(7.3)
Absent	19.21	637.90	(2.1)	751.79	(6.3)	850.23	(11.5)
				Short target			
Present	44.55	621.82	(1.0)	887.07	(1.0)	1114.33	(6.3)
Absent	29.31	613.98	(3.1)	792.03	(10.4)	938.28	(6.3)

Note. The values in parentheses represent error percentages. The stimuli were letters (pb) and the length difference was two pixels (8 pixels versus 6 pixels). The loops were small.

30.64, $p < .01$] and the array size [$F(2,14) = 88.98, p < .01$] were highly significant, yet there was no difference in the trial condition per se [$F(1,7) = 1.58, p < .25$].

In planned comparison analyses, the slope difference between positive versus negative trials (ratio = 1 : 1.72) reached borderline significance for the long target [$F(1,7) = 4.5$, $p < .08$], and was significant (ratio = 1 : 0.66) for the short target condition [$F(1,7) = 8.3$, $p < .03$].

For the non-letter arrays (see Table 11), the slopes were 13.60 ms (positive) and 34.15 ms (negative) with the ratio of 1 : 2.51 for the long target conditions; 52.66 ms (positive) and 86.04 ms (negative) with the ratio of 1 : 1.63 for the short target conditions. The three way interaction was not significant [$F(2,14) = 1.08, p < .36$]. But, the two way interaction between trial condition (positive/negative) and array size was significant [$F(2,14) = 12.54, p < .01$], and the interaction between target condition (long/short) and trial condition (positive/negative) was not [$F(1,7) = 2.1, p < .19$]. Therefore, the search time difference between the trial conditions seems to be similar for the long and the short target conditions. With the target conditions collapsed together, the mean slopes were 33.13 ms and 60.10 ms for the positive and the negative trials, respectively (ratio = 1 : 1.8). In a planned comparison, the linear interaction between the positive and the negative trials (equal weight of 1, 1 for the long and the short target conditions) was highly significant [$F(1,7) = 14.36, p < .01$].

All main effects were significant. Response to the bigger array size were slower than to the smaller ones [$F(2,14) = 102.12, p < .01$]; the positive trials were faster than the

Table 11.

Slope ratios for the letter and non-letter groups as a function of the target conditions, discriminability levels and loop sizes.

		long			short		
pixel	loop	Present	absent	ratio	Present	absent	ratio
				letter			
2	large	18.80	37.19	1 : 1.98	50.75	39.14	1 : 0.77
2	small	11.19	19.21	1 : 1.70	44.45	29.31	1 : 0.66
3	small	10.79	19.95	1 : 1.85	55.12	55.67	1 : 1
				non-letter			
2	large	8.04	50.08	1 : 6.23	54.35	89.66	1 : 1.65
2	small	13.60	34.15	1 : 2.51	52.66	86.04	1 : 1.63
3	small	8.37	21.58	1 : 2.58	32.12	80.01	1 : 2.49

Note. The ratios are present to absent slopes.

negative trials [$F(1,7) = 55.38, p < .01$]; and to find the longer target was easier than to find the shorter target [$F(1,7) = 20.40, p < .01$].

To conclude, for the letter arrays the negative trials were slower than the positive trials in the long target condition, and actually became faster than the positive trials (1 : 0.66) in the short target condition. For the non letter arrays, the search difference between positive and negative trials yielded an overall ratio of 1 : 1.8 over the different target conditions.

Discussion

Figure 22 shows the comparisons of the RT data for Experiments 10 and 11, and Table 12 shows the comparisons of slope values for all six experiments (from Experiment 6 to Experiment 11). Considering that all the six experiments employed different subjects, the similarity between the slope ratios is quite remarkable.

For the letter arrays, although overall search speed increased with the small loop size, the ratios of the positive to the negative trials are virtually identical between the groups that used the line length difference of two pixels with the large loops and the groups that used the same two pixel differences but with the small loops. For the non-letter arrays, the anomaly of 1 : 6.23, found for the long target condition of "non-pb" (Experiment 7) that employed two pixel difference and large loop size, makes the comparison not quite valid. However, at least in the short target condition, the ratios are again virtually identical between groups of two pixels, large loop (1 : 1.65) and two

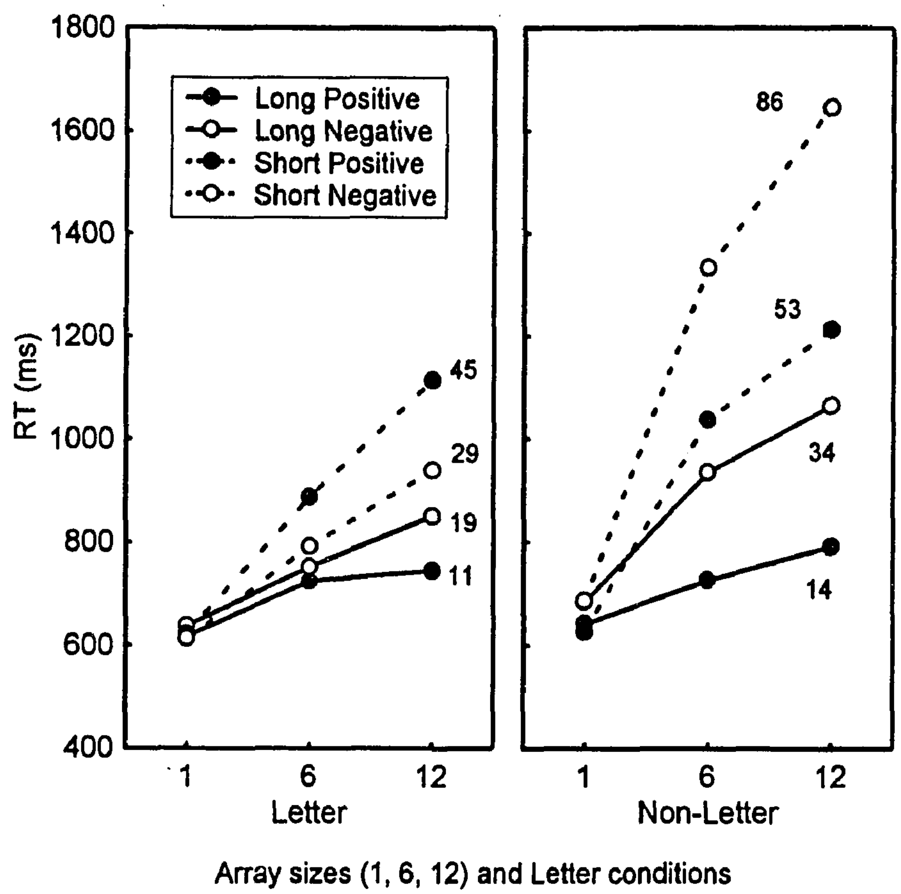

Figure 22. Mean RTs as a function of array sizes and target conditions in Experiment 10 (pb) and Experiment 11 (non-pb). The lines were eight and six pixels long. The loop sizes were small. The numbers on the graphs represent slope values.

Table 12.

Mean RTs and slopes as a function of array size in Experiment 11.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	13.60	642.00	(2.1)	726.13	(1.0)	792.50	(4.2)
Absent	34.15	684.75	(1.0)	935.25	(0.0)	1065.13	(2.1)
				Short target			
Present	52.66	626.25	(1.0)	1037.50	(13.5)	1214.25	(20.8)
Absent	86.04	686.75	(3.1)	1334.25	(13.5)	1646.00	(13.5)

Note. The values in parentheses represent error percentages. The stimuli were non-letters (non-pb) and the length difference was two pixels (8 pixels versus 6 pixels). The loops were small.

pixels, small loop (1 : 1.63). Therefore, the size of the loop does not seem to play an important role in the relationships among the search conditions. Although the level of discriminability (two pixel versus three pixel) does seem to change the data patterns, primarily in the short target conditions, the differences were not significant.[25]

The most consistent and noticeable effect in Table 12 is that in all 12 conditions, the ratio of the positive to negative is always smaller in letter arrays than in non-letter arrays. The degree by which the ratio is smaller is more salient in the short target conditions. Even though some of these differences are statistically significant and some are not, as examined in detail in various discussion sections so far, it is clear that the overall tendency is consistent.

The only condition where Treisman's search asymmetry was unambiguously replicated was when the pixel difference was 4 (Experiment 3). This was the condition where the discriminability was so high that, at least in the case of long lines, target detection could have been based on subjective "pop-out." If the relationship between features and conjunctions is strictly bottom-up and the nature of the visual context of features does not have much impact on processes in early vision, a very easily discriminable line length as a target feature would minimize any burdens on the system

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[25] Comparing the short target conditions in two pixel, small loop with those in three pixel, small loop, the negative trials became slower (from 1 : 0.66 to 1 : 1 in the letter array, 1;1.63 to 1 : 2.49 in the non-letter array). However, the difference was not significant ($F(2,28) < 1$) in ANOVA with pixel conditions (2,3) as IV and the target-present/target-absent and array size as DV.

due to overhead processes for the loops. The data patterns of letter and non-letter arrays then should resemble those of the line Experiment 3, and be comparable in terms of the change due to the addition of the loops. Consequently, the experiments should produce unambiguous results for the absence of a familiarity effect. In that sense, the four pixel difference could be the most conservative and rigorous test of a contextual effect in early vision. The following two experiments were replications of Experiments 10 and 11 using a four pixel difference.

Experiments 12 and 13 (pixel 9 : 5)

Method

Stimuli. Stimuli (see Figures 23 and 24) were constructed as described in Experiments 10 and 11. The long line length was nine pixels (approximately 9 mm) and the short line remained as five pixels (approximately 5 mm). The same loop size (three pixels wide and high) was used.

Subjects. 8 subjects were recruited from the Institute for Basic Research for the letter group, and another 8 subjects from the College of Staten Island for the non-letters. The students were paid 3 dollars for participation and rewarded with extra credits for their introduction to psychology course.

Results

For "pb" arrays, the slopes were 8.26 ms (positive) and 9.07 ms (negative) in the long target (the ratio of 1 : 1.09), and 29.41 ms (positive), 41.37 ms (negative) in the

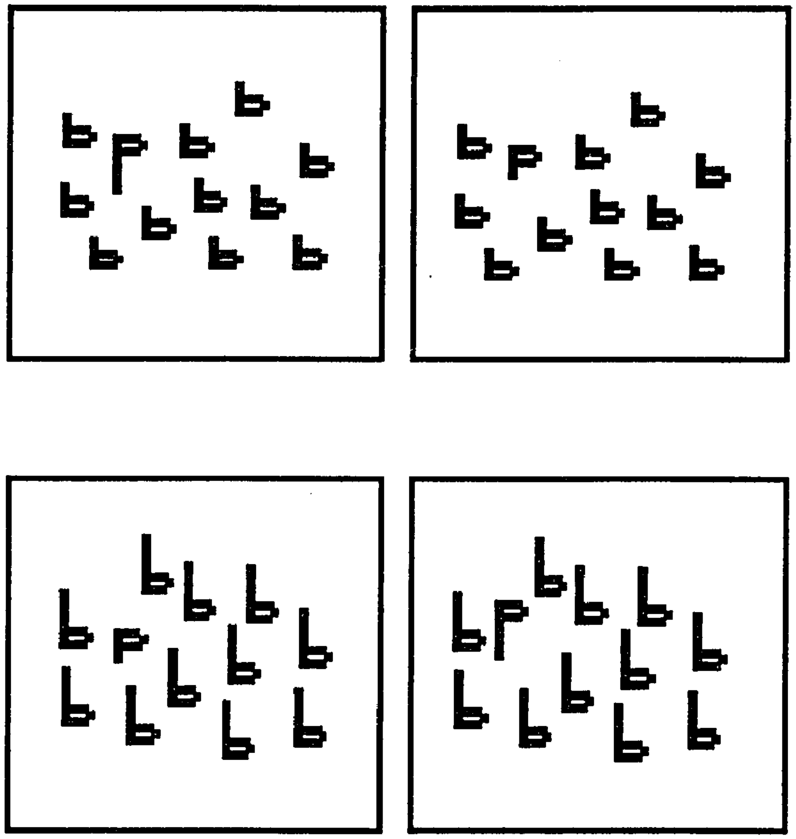

Figure 23. Examples of the long and the short target conditions for array size 12 in Experiment 12 (pb). The long and the short lines were nine and five pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version. The loop size was small.

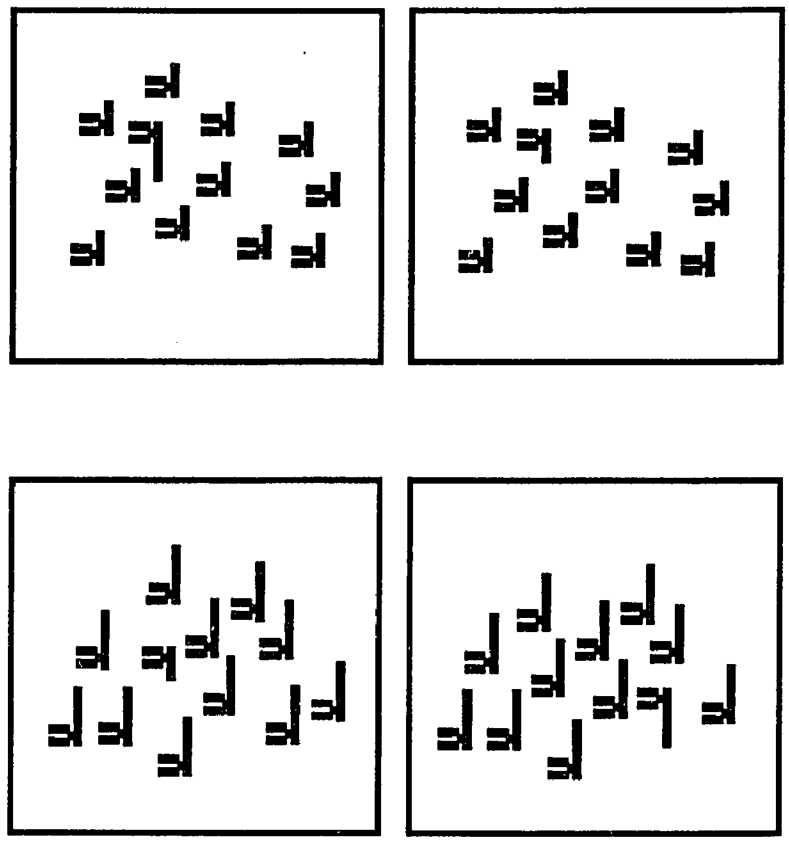

Figure 24. Examples of the long and the short target conditions for array size 12 in Experiment 13 (non-pb). The long and the short lines were nine and five pixels long, respectively. The top panels show the long target present array on the left and its absent array on the right. The bottom panels show the short target version. The loop size was small.

short target conditions (the ratio of 1 : 1.41). The relative differences in the slopes between the target conditions were not significant (three way interaction, $F(2,14) = 1.31$, $p < .30$). In separate planned analyses for the long and the short target conditions, the slope differences between the positive and the negative trials were not significant either (for the long target condition, $F(1,7) < 1$; for the short target condition $F(1,7) = 2.73$, $p < .15$). Table 13 shows mean RTs, slopes and error data for the "pb" arrays. With target conditions collapsed, there was no two way interaction of trial condition and array size [$F(2,14) = 2.44$, $p < .13$]. With array size collapsed, the search time difference between the positive and the negative trials was the same for the long and the short target searches (two way interaction between trial and target, $F(1,7) < 1$). The short target condition got more difficult than the long target condition did as the array size got bigger [$F(2,14) = 66.16$, $p < .01$]. All three main effects were significant ($p < 0.001$).

Thus, as in the experiment of three pixel difference, the overall reaction time for the short target condition was slower than for the long target condition, but there was no difference between the positive and the negative trials within the target conditions. The average slopes were 8.67 ms for the long target and 35.39 ms for the short target condition.

On the other hand, the differences between search conditions were highly significant in the non-letter array. The slopes (see Table 14) were 4.14 ms for the long target, positive trials, 9.82 ms for the long target, negative trials (ratio = 1 : 2.37); 27.26 ms for the short target, positive trials, 73.90 ms for the short target, negative trials (ratio = 1 :

Table 13.

Mean RTs and slopes as a function of array size in Experiment 12.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	8.26	514.91	(1.0)	573.68	(2.1)	606.75	(6.3)
Absent	9.07	575.92	(2.1)	671.49	(3.1)	678.67	(2.1)
				Short target			
Present	29.41	522.16	(2.1)	752.67	(6.3)	850.53	(16.7)
Absent	41.37	603.04	(2.1)	875.28	(1.0)	1062.01	(2.1)

Note. The values in parentheses represent error percentages. The stimuli were letters (pb) and the length difference was four pixels (9 pixels versus 5 pixels). The loops were small.

Table 14.

Mean RTs and slopes as a function of array size in Experiment 13.

		Array size					
Condition	Slope	1		6		12	
				Long target			
Present	4.14	568.50	(1.0)	574.50	(0.0)	613.13	(1.0)
Absent	9.82	619.00	(1.0)	655.63	(2.1)	726.25	(0.0)
				Short target			
Present	27.26	641.50	(2.1)	808.38	(5.2)	943.13	(10.4)
Absent	73.90	711.88	(1.0)	1130.13	(0.0)	1527.63	(3.1)

Note. The values in parentheses represent error percentages. The stimuli were non-letters (non-pb) and the length difference was four pixels (9 pixels versus 5 pixels). The loops were small.

2.71). The three way interaction was significant [$F(2,14) = 26.44$, $p < .01$]. In planned analyses, the slope difference between the positive versus negative trials was marginally significant for the long target condition [$F(1,7) = 4.41$, $p < .07$], and highly significant for the short target condition [$F(1,7) = 33.78$, $p < .01$]. With array size collapsed, the size of the difference between the positive trials and the negative trials was significant [$F(1,7) = 22.43$, $p < .01$]. The search speed decreased more in the short than the long target condition as the array size increased [$F(2,14) = 21.86$, $p < .01$]. The search speed for the negative trials decreased more rapidly than that for the positive trials over increasing array sizes [$F(2,14) = 21.51$, $p < .01$].

To conclude, for the letter arrays the reaction times are not slower for the negative trials than for the positive trials in either target condition, and for the non-letter arrays the search speed was always slower for the negative trials than for the positive trials.

Discussion

As in the all previous experiments, the difference between the positive and the negative trials was smaller in the letter arrays than it was in the non-letter arrays. The ratios are 1 : 1.10 (long target), 1 : 1.41 (short target) for the letter arrays and 1 : 2.37 (long target), 1 : 2.71 (short target) for the non-letter arrays.

In Experiments 12 and 13, the long target conditions' slopes were very shallow for both the letter and the non-letter arrays (see Figure 25). If the data are compared with those of Experiment 3 (line, 4 pixel), the non-letter arrays show very similar patterns to the line data. In both the line and the "non-pb" arrays, the search time for the long target

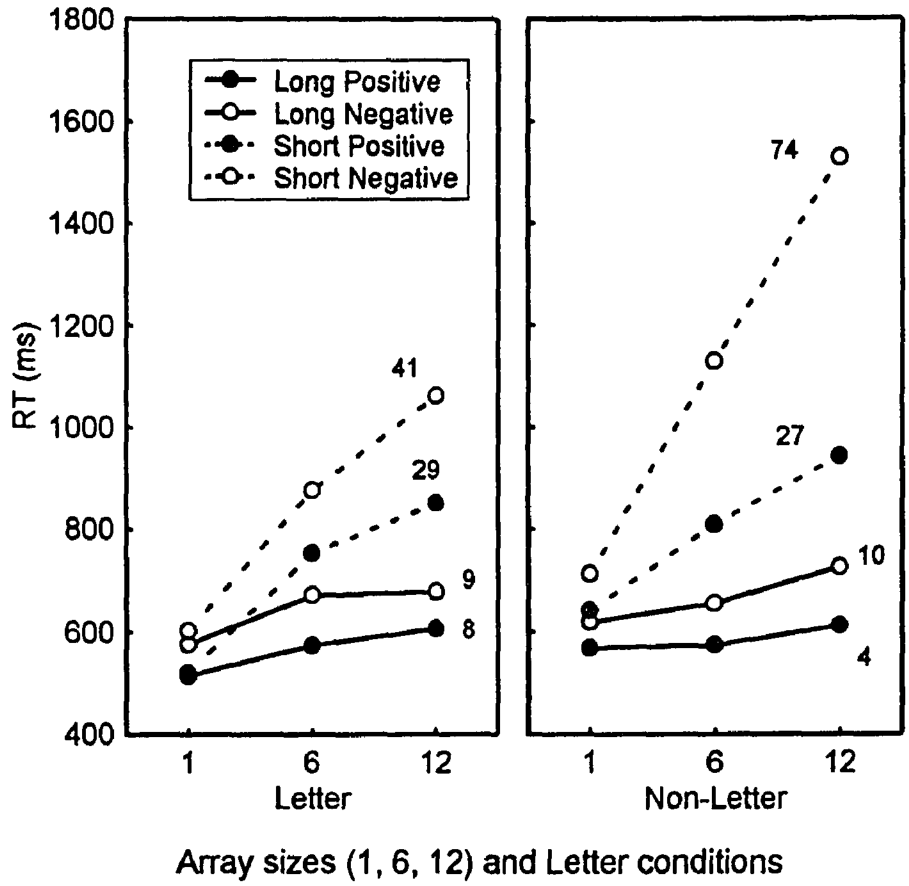

Figure 25. Mean RTs as a function of array sizes and target conditions in Experiment 12 (pp) and Experiment 13 (non-pp). The lines were nine and five pixels long. The loop sizes were small. The numbers on the graphs represent slope values.

was extremely fast (6 ms for the line, 4 ms for the "non-pb"), and the negative trials took twice as long (13 ms for the line, 9 ms for the "non-pb"). With planned comparisons, the significance levels of the positive and the negative slopes were $p < .004$ for the line and $p < .07$ for the "non-pb" .

The short target conditions were less similar, but quite comparable in the line and the "non-pb" arrays. The search rates were faster in the line array (12.48 ms for positive trials, 27.38 ms for negative trials) than they were in the "non-pb" (27.26 ms for positive trials, 73.90 ms for negative trials). The ratio (positive/negative) was 1 : 2.19 in the line array compared to 1 : 2.71 in the "non-pb" array. However, the error rate for array size 12 in the positive trials is quite high compared to the rest of the "non-pb" arrays (see Table 14). If subjects had tried to maintain similar error rates of about 3 or 4 %, the slope values (of the positive trials) would have increased, which would reduce the size of the ratio 1 : 2.71. Therefore, it is not unreasonable to conclude that the "non-pb" data closely resemble the line data.

The letter array data were different (see Figure 26). Search for the long target, when present, was equally fast (8 ms) as the line and the "non-p" arrays, but the decision making for the target's absence was not any slower than the detection of the target itself (9 ms). This lack of difference between the two trial conditions was maintained in the short target condition also, though to a less degree. The search rate to find the short target was 30 ms, whereas to decide it was absent (according to experiment's definition of target-absent condition) took 41 ms.

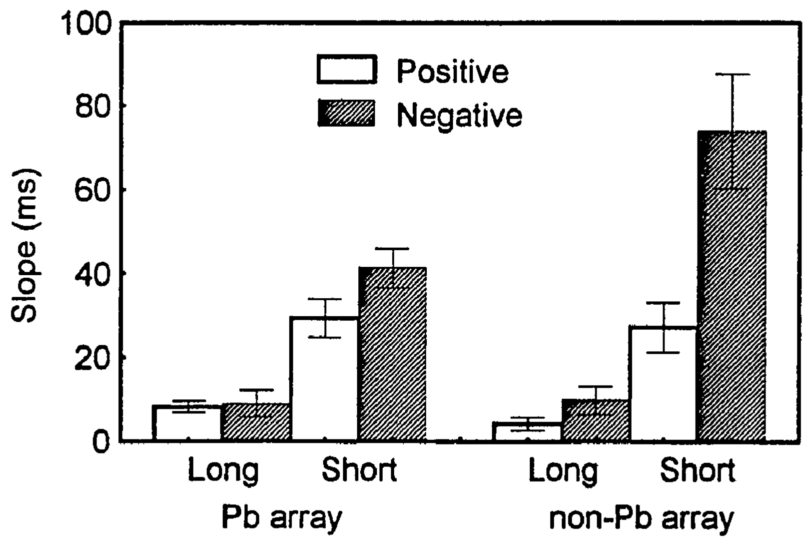

Figure 26. Comparisons of slopes (mean ± SE) of the positive and the negative trials for the long and the short target conditions in Experiments 12 and 13. The lines were nine and five pixels long. The loop sizes were small.

What is interesting is that the overhead burdens of processing the loop features seem to operate only in the short target condition. In other words, in the long target condition, the "non-pb" array data show that subjects were able to ignore the loop features completely. There is virtually no difference between the slopes of the line arrays (6 ms for the positive and 13 ms for the negative trials) and those of the "non-pb" arrays (4 ms for the positive, 9.8 ms for the negative trials) for the long target conditions. The very shallow slopes also indicate that the search was probably conducted at preattentive stage. Thus, if the salience of the target item is very high, and consequently the detection of the target can be processed without focused attention, the irrelevant features obviously do not exert much influence on the processing system. This is then a clear evidence that the search for the long target condition of the "non-pb" arrays was conducted on the basis of line feature maps' activation levels.[26]

The long target "non-pb" data, in turn, attest that the search in the same condition for the "pb" arrays was also proceeded on the basis of the line maps' activation. The level of salience, the number of items, and the involved features, all are the same in both arrays. The search data of the two arrays together then are strong evidence that the lines in "pb" arrays are, as hypothesized, not the same lines as in "non-pb" arrays, because unlike in the "non-pb" arrays, there is no difference in search slopes for "pb" arrays (8 ms versus 9 ms, for the positive and the negative trials, respectively). The short line of

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[26] To put it in different terms, the "non-pb" search results clearly indicate that the long target condition is not a case of conjunction search.

"p" in the negative trials (the same length as the lines in distractor "b"s) took on a qualitatively different nature and became an odd item that was different from the lines of "b"s. Consequently, there was no need to conduct an exhaustive search in the negative trials of "pb" arrays (resulting in similar slopes) as there was in the negative trials of "non-pb" arrays (resulting in the slope ratio of 1 : 2).

For the short target conditions, the loops made the search more difficult. However, the relative difference between the positive and the negative trials over "pb" and "non-pb" arrays was maintained. Again the search slopes were similar for "pb" arrays, but the slope for the negative trials was much larger than the slope for the positive trials for "non-pb" arrays. In both arrays, the search data of the array size 12 in the positive trials show considerably higher error rates (16.7 % in "pb" and 10.4 % in "non-pb")[27] compared to the other search conditions (range from 0 % to 6 %). These error data patterns indicate that subjects could have 'prematurely' terminated the searches in the arrays containing 12 items. Thus subjects might have searched only a certain proportion of the 12 items and responded negatively if the target still was not found. This strategy would yield correct answers for the negative trials at the expense of increased error rates

[27] A half of the 16.7% error rate (in "pb") came from a single subject who seems to have responded negatively to all the trials of the array size 12 for the short target condition. With the subject's data excluded, the slope values were 29.13 ms and 37.86 ms for the positive and the negative trials, respectively.

in the positive trials.[28] Therefore the true slope values could be higher than the values the data show. However, since both search slopes will increase (for both positive and negative trials, the number of items to examine would increase in order not to terminate the search prematurely), the relative difference between the positive and the negative trials will be preserved.

The results show that, even in this high level of discriminability, letters and non-letters are not perceived and processed in the same fashion. The non-letter arrays were similar to the line arrays, but the letter arrays were different from both. For all three types of arrays, line, letter and non-letter, the short target conditions were more difficult than the long target conditions in general. But whereas subjects in the line and the non-letter arrays utilized exhaustive search for the negative trials, subjects in the letter arrays did not. The search speed for the target-present trials and the target-absent trials were comparable for the letter array tasks.

Statistical Comparisons Across Experiments

All experiments were run as conceptually related but separate experiments. However, the uniformity of experimental settings, stimulus configurations and testing conditions permit statistical analyses treating the experiments as a between groups factor within an analysis of variance context. Therefore, nine experiments were reanalyzed as

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[28] Subjects would 'miss' the target in the positive trials if the target happened to be the item subjects did not examine, whereas their 'negative' response would be always correct for the negative trials.

three groups of line, letter and non-letter, each employing a four way between subjects design (discriminability × target condition × trial condition × array size). The added variable of discriminability had three levels reflecting variation in the line length difference (two, three, and four pixels) between target and distractors in the three experiments of each group. Only the results of the statistical analyses are presented in this section and their implications are examined in the following General Discussion. All analyses tables are presented in the Appendix B.

Line Arrays

Experiments 1, 2 and 3 (line length difference between target and distractors of two, three, and four pixels, respectively) were analyzed together as three levels of a between-subjects factor, discriminability. The four way interaction was significant [$F(4,42) = 2.76$, $p < .04$]. Thus, the relationships between the target, the trial and the array size were not equal over three discriminability levels (see Figure 27). To find out the source of the significant interaction, the long and the short target conditions were examined separately in two three way analyses of variances (discriminability × trial condition × array size).

There was no three way interaction of discriminability level (pixel difference of 2, 3, and 4 in line length) by trial condition (positive/negative) by array size in the long target condition [$F(4,42) = 1.67$ $p < .18$]. The two way interaction of trial condition by array size was highly significant [$F(2,42) = 7.69$, $p < .01$]. Thus, the negative trials were significantly slower than the positive trials over larger array sizes, yet the line length

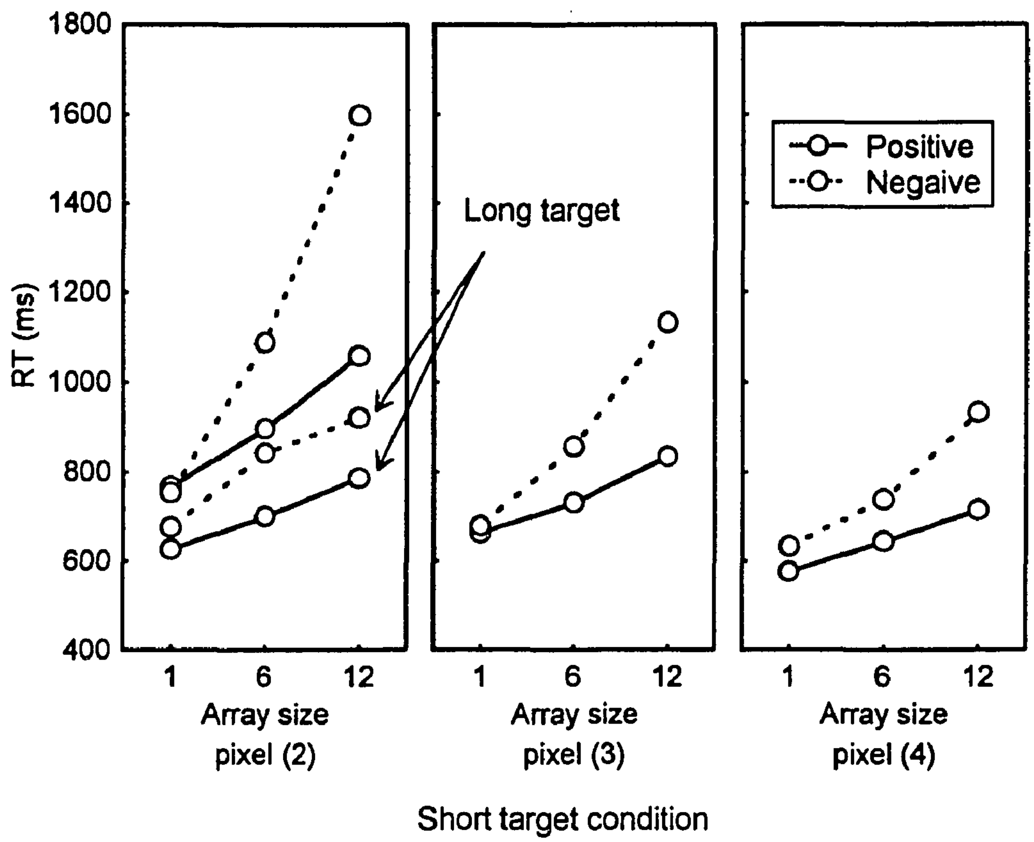

Figure 27. Comparisons of mean RT data fro the line Experiments 1, 2, and 3. The long target conditions are mean RTs from all three experiments. The short target conditions are shown separately for each experiment.

difference of target and distractors did not matter. The mean positive slope was 14.41 ms and the mean negative slope was 21.93 ms (slope ratio of 1 : 1.5). A main effect of discriminability was significant [$F(2,21) = 9.25, p < .01$]; the larger the difference between targets and distractors the faster was reaction time.

On the other hand, the level of discriminability was significant for the short target condition [$F(4,42) = 3.15, p < .03$]. Thus, if the target was short, the difference between the positive and the negative trials changed significantly depending on the size of difference between targets and distractors. The ratios of the slopes for the positive and negative trials were 1 : 2.9 for the two pixel condition, 1 : 2.6 for the three pixel condition, and 1 : 2.2 for the four pixel condition, respectively (see Figure 8, short target conditions). Thus, when there was only a small difference between the target and the distractors, negative trials were particularly difficult. When the discrimination became easier as in four pixel condition, the ratio approached 1 : 2. The level of discriminability itself was also highly significant [$F(2,21) = 8.48, p < .01$]. As was in the long target condition, the overall reaction time became faster for the larger difference between target and distractors.

The asymmetry of the positive trials did not emerge with the three line experiments combined. When the positive trials in the long and the short target conditions were examined separately in a three way analysis of variance, there was no significant interaction between the two positive trials and 3 different discriminability levels [$F(4,42) < 1$]. There was no two way interaction between the two positive trials and array size either [$F(2,46) = 1.45, p < .25$]. Nor was there a significant planned comparison of their linear interaction [$F(1,23) = 2.27, p < .15$]. Thus, the significant asymmetry that appeared in the four pixel line arrays (Experiment 3) was not preserved when the three experiments were reanalyzed together.

To summarize, overall reaction time became faster as the discrimination of target line from distractor lines became easier. The effect of discriminability upon the difference between the positive and the negative trials appeared to be specific to the short target condition. To decide that the short target was absent was much more difficult if the line length difference between target and distractors was small. The same decision for the long target was not affected by the line length differences. The asymmetry for the positive trials was not significant; to find the shorter target among longer distractors was not more difficult to find the longer target among shorter distractors.

Letter Arrays

Experiments 8, 10 and 12 ("pb" experiments with line length differences of three, two, and four pixels, respectively) were compared to examine the effect of varying discriminability.

There was no significant four way interaction [$F(4,42) = 1.94, p < .12$]. The three way interaction between target condition (long/short), trial condition (positive/negative), and array size was not significant either [$F(2,46) < 1$]. The two way interaction of trial condition (positive/negative) by array size was not significant [$F(2,46) < 1$], however, the two way interaction of target condition (long/short) by array size was highly significant [$F(2, 46) = 73.95, p < .01$]. The level of discriminability itself was not significant at probability level of .05 [$F(2,21) = 3.04, p < .07$].

Therefore, for letter arrays, the overall effect of discriminability appears to be only marginal and the reaction time speeds for various conditions were not influenced by the line length difference between targets and distractors (see Figure 28). Moreover, there was no significant overall difference in reaction time speed between the positive and negative trials either for the long target or for the short target condition. Thus, overall, the short target condition was more difficult than the long target condition, but there was no difference between the positive and the negative trials within each target condition. This data pattern was not affected by the level of discriminability.[29]

The asymmetry was tested in a separate three way analysis of variance. The three way interaction of discriminability by trial (the positive trials in the long and short target conditions) by array size was significant [$F(4,42) = 3.90, p < .01$]. The three separate planned comparisons of the linear interaction for each level of discriminability were highly significant also [$F(1,21) = 45.50, p < .01$ for pixel 2; $F(1,21) = 79.86, p < .01$ for pixel 3; $F(1,21) = 18.95, p < .01$ for pixel 4]. The mean slopes for the positive trials in the long and short target conditions were 11.18 ms and 44.55 ms, respectively, for pixel

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[29] Collapsing the trial conditions and the level of discriminability together, the mean long target slope was 13.08 ms and the mean short target slope was 42.57 ms.

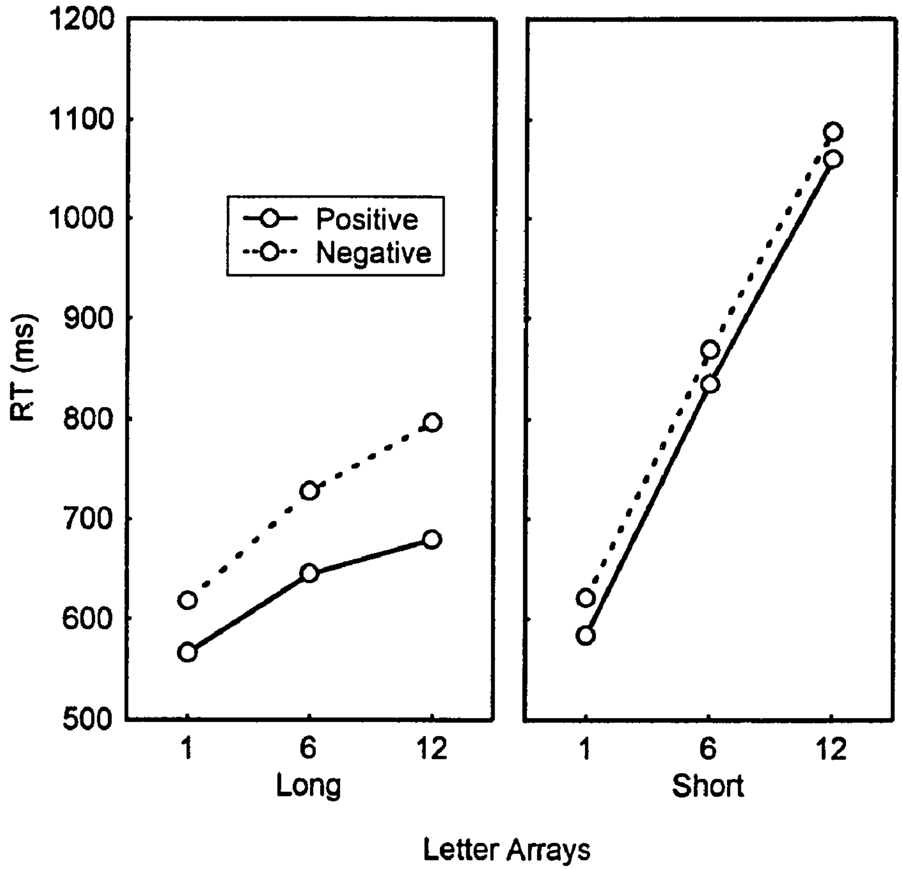

Figure 28. Comparisons of mean RTs for the long and the short target conditions of the letter arrays. RTs are the mean values of Experiments 8 (pixel 3), 10 (pixel 2), and 12 (pixel 4). The loop sizes were small in all three experiments.

differences of 2; 10.79 ms and 55.12 ms for pixel difference of 3; and 8.26 ms and 43.03 ms for pixel difference of 4. [30]

Non-Letter Arrays

Experiments 9, 11 and 13 ("non-p/non-b" experiments with line length differences between target and distractors of three, two, and four pixels) were treated as three levels of the discriminability variable.

The four way interaction among discriminability, target, trial, and array size was not significant [$F(4,42) = 1.77, p < .16$]. As in the letter arrays, the main effect of discriminability was not significant [$F(2,21) = 2.85, p < .09$]. However, the three way interaction of target (long/short) by trial (positive/negative) by array was highly significant [$F(2,42) = 21.01, p < .01$]. This interaction was further analyzed in two way analyses of variance for the long and short target conditions separately with the three levels of discriminability collapsed together. The interaction of trial condition (positive/negative) by array size was highly significant for the long target condition [$F(2,46) = 15.68, p < .01$] and for the short target condition [$F(2,46) = 45.03, p < .01$]. Planned comparisons employing linear coefficients for arrays were also highly significant

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[30] Although the differences were highly significant, the effect of discriminability on the size of the difference (how much more difficult the positive trials of the short target condition was compared to the ones in the long target condition depending on the level of discriminability) does not bear a particular importance for the current experiments. Unlike the ratio of the positive and the negative trials, there is no particular underlying mechanism that deals with the effect in Treisman's model. The strength of the effect alone suffice.

[$F(1,23) = 23.01$, $p < .01$ for the long target; $F(1,23) = 57.14$, $p < .01$ for the short target]. The mean slope of the positive trials for the long target was 8.7 ms, and of the negative trials was 21.85 ms (the slope ratio of 1 : 2.5). The mean slope of the positive trials for the short target was 37.35 ms, and of the negative trials was 79.98 ms (the slope ratio of 1 : 2.1).

As in the letter arrays, the effect of the asymmetry was tested in a three way analysis of variance (discriminability × trial × array), with positive trials in the long and the short target conditions. The three way interaction was not significant [$F(4,42) = 1.23$, $p < .19$]. However, the two way interaction of the trial condition by array size was highly significant [$F(2,42) = 42.07$, $p < .01$]. Thus, to find the short target was much more difficult than to find the long target (the mean slopes of 8.7 ms versus 37.35 ms), and the level of the difficulty was not affected by the level of discriminability (see Figure 29).

Thus, for non-letters, like letter arrays, the effect of discriminability level overall seems to be only marginal, but unlike letter arrays, non-letter negative trials always were more difficult than the positive trials both in the long and the short target conditions. The asymmetry was as strong as it was for letter arrays, however the size of the asymmetry was not influenced by the level of discriminability. Figure 30 shows the mean data of the letter and the non-letter arrays together for direct comparison.

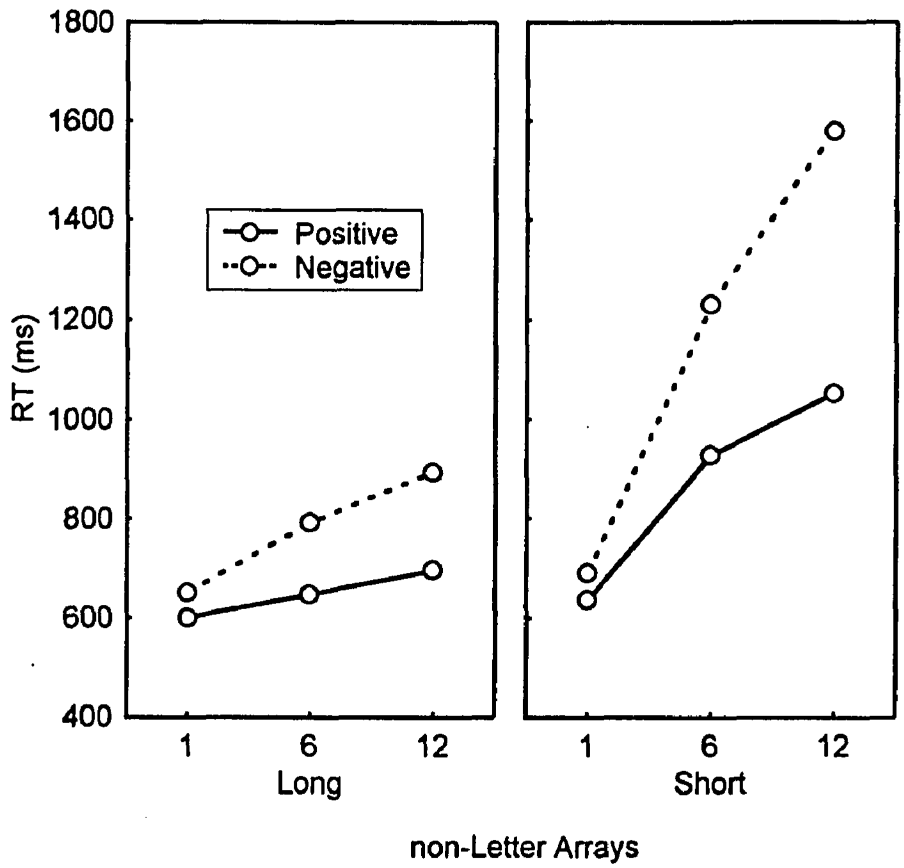

Figure 29. Comparisons of mean RTs for the long and the short target conditions of the non-letter arrays. RTs are the mean values of Experiments 9 (pixel 3), 11 (pixel 2), and 13 (pixel 4). The loop sizes were small in all three experiments.

General Discussion

In this thesis, the issue of familiarity's effect in early vision was examined within the framework of Treisman's pooled response model (Treisman & Gormican, 1988). With a general notion that component features are not affected by each other within unfamiliar contexts and they may be within familiar contexts, two specific hypotheses were proposed: (a) data patterns for non-letter arrays would be similar to those of line arrays, yet overall response rates would be slower in non-letter arrays than in line arrays; (b) the search rates of the positive and the negative trials would be similar to each other in letter arrays, and when they were different, the degree to which they differ would be less than that of non-letter arrays of similar configurations.

The first hypothesis seemed to be confirmed only for the short target conditions. Table 15 shows search rates and ratios for the six line and non-letter experiments that used different line lengths and small loops. The ratios in the short target conditions indicate that overall the line and the non-letter arrays generated similar patterns of positive/negative search rates.

There is a general tendency to make fewer errors in the negative trials than in positive trials for displays of array size 12 in all searches for the short target conditions. The tendency seems to indicate that subjects were prematurely terminating the search if the array size is large. As discussed in Experiments 12 and 13, premature termination

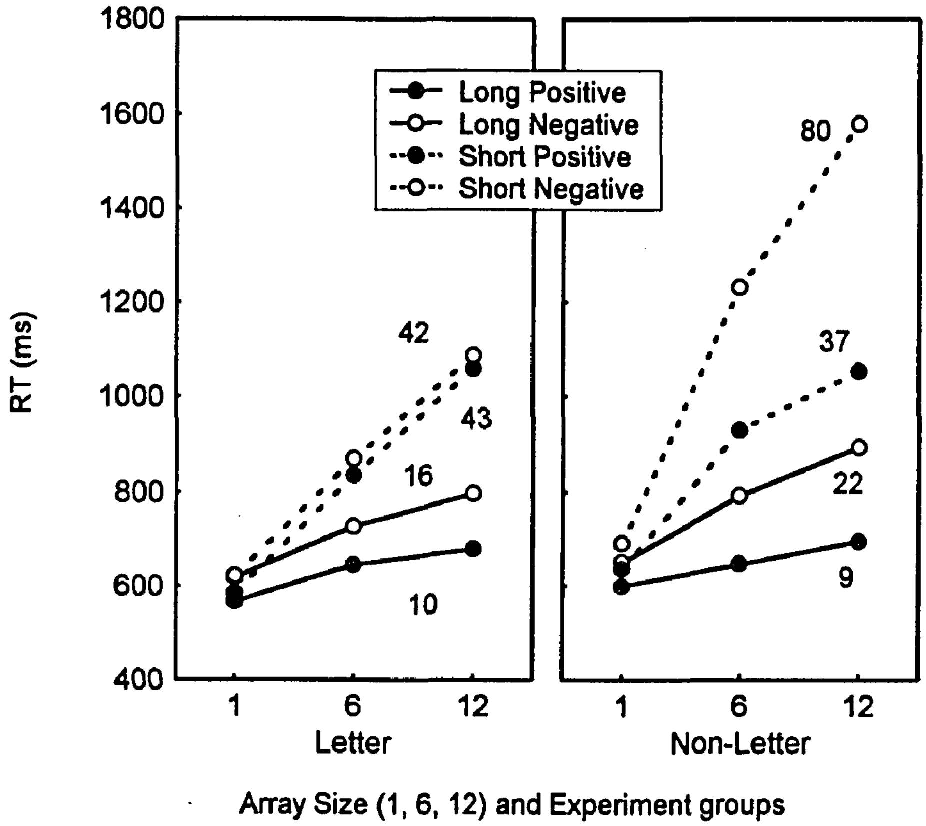

Figure 30. Mean RTs as a function of array size and target conditions for the letter and the non-letter arrays. The numbers on the graphs represent slope values. RTs and slope values are the mean values of three letter (Experiments 8, 10, and 12) and three non-letter experiments (Experiments 9, 11, and 13).

Table 15.

Slope ratios for all line and non-letter experiments.

	long			short		
Group	Present	absent	ratio	Present	absent	ratio
			2 pixel			
line	18.80	37.19	1 : 1.98	50.75	39.14	1 : 0.77
non-letter	11.19	19.21	1 : 1.70	44.45	29.31	1 : 0.66
			3 pixel			
line	18.80	37.19	1 : 1.98	50.75	39.14	1 : 0.77
non-letter	11.19	19.21	1 : 1.70	44.45	29.31	1 : 0.66
			4 pixel			
line	18.80	37.19	1 : 1.98	50.75	39.14	1 : 0.77
non-letter	11.19	19.21	1 : 1.70	44.45	29.31	1 : 0.66

Note. All non-letter arrays reported used small loops.

could mean that the true slope values might have been larger since subjects would have spent more time to examine the entire arrays. However, what is important in the context of these experiments is not the absolute slopes themselves, but the difference between the slopes of the positive and the negative trials and that difference can not be estimated since the true slope values are unknown.

Figure 31 shows the slope values that were computed based only on the first two arrays of size 1 and 6. With smaller array sizes, the number of items to examine is too small for premature termination and accordingly the error rates were low. Although the overall slope values were larger when only the two array sizes 1 and 6 were included, as the two histograms in Figure 31 show, the overall pattern of slope differences between the various conditions is virtually identical to the pattern obtained from all three array sizes. Thus, the present analyses seem to be valid despite the differential error rates between the positive and the negative trials of the array size 12.

The slope values themselves were larger for the "non-pb" arrays than for the line arrays as hypothesized. However, this also is evident only in the short target conditions (see Table 15). For the long target conditions, the positive trials show similar slope sizes for the line and the "non-pb" arrays except for the arrays of the lowest discriminability (2 pixel); and the size differences in the negative trials are not consistent across different levels of discriminability.

The ratios for the long target conditions are larger in the non-letter arrays because the line arrays did not reach 1 : 2 ratio while the non-letter arrays went beyond 1 : 2

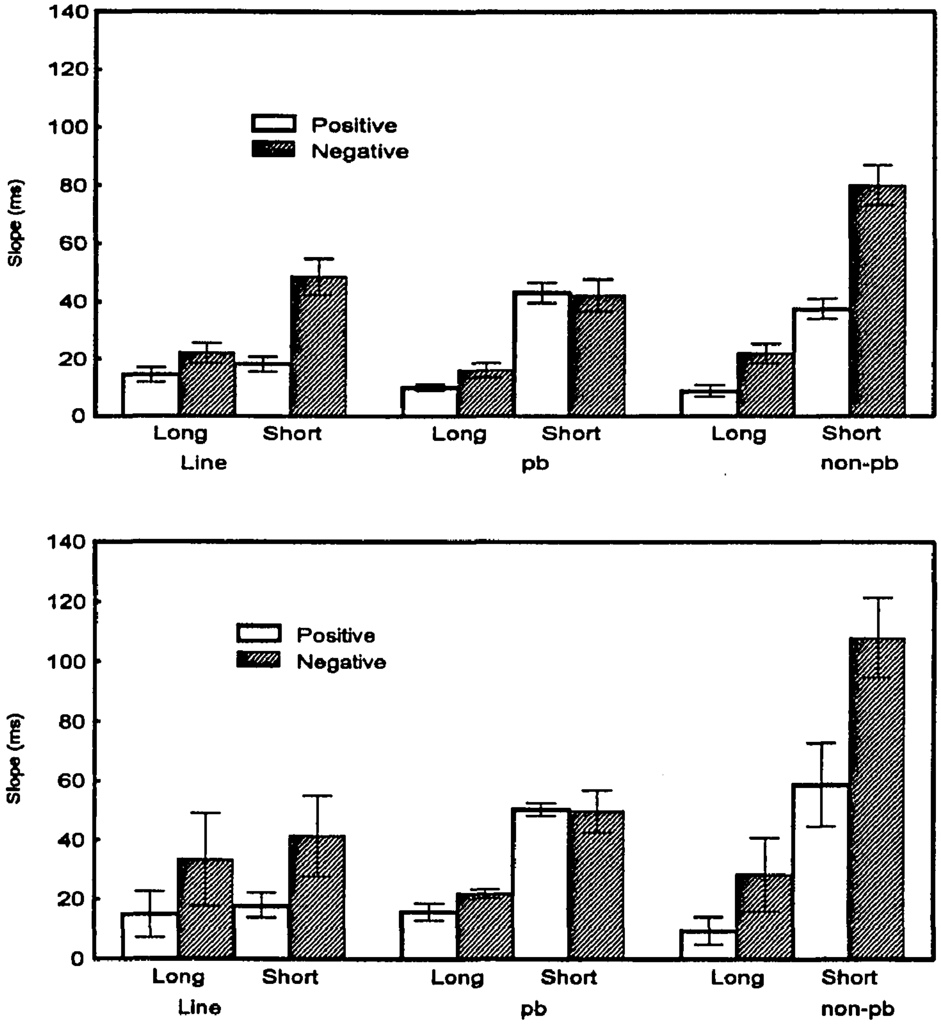

Figure 31. Mean slopes for the long and the short target conditions of the "line', "pb", and "non-pb" arrays. The data are the mean values of the nine experiments (Experiments 1, 2, and 3 for the "line", Experiments 8, 10, and 12 for the "pb", Experiments 9, 11, and 13 for the "non-pb"). The top panel shows the slopes for all three array sizes 1, 6, and 12. The bottom panel shows the slopes computed with the array size 1 and 6 (size 12 was excluded).

ratio. In fact, the ratios of the positive to negative trials have similar values in all conditions of the non-letter arrays regardless of target conditions. Had the line experiments successfully replicated Treisman's original line experiment (Treisman & Gormican, 1988) the results of the long target conditions in the non-letter arrays would also have confirmed the hypothesis. In other words, it is not clear whether the current line experiments simply failed to replicate Treisman's for some unknown reasons, or there indeed is some qualitative difference between long and short target conditions that is not quite predicted by Treisman's model.

For instance, as discussed in the section of Statistical comparisons across experiments, the level of discriminability in the line arrays had its effect primarily on the short target conditions (see Figure 8). In the long target conditions, although overall search speed increased as the line length difference became larger, the interaction between trial condition and array size did not reach statistical significance over different levels of discriminability.

The addition of loops also seems to have differential effects when the target is longer and when it is shorter. Overall, the loops consistently make the short target conditions more difficult for both the positive and the negative trials, but in the long target conditions positive trials either do not change much or become faster (see Table 16). Although the differences are not always statistically significant (see Tables 16 and 17 for slope values and their probability levels), Table 18 and Figure 32 reveal that the differential effect of loops in letter and non-letter arrays is not as obvious in the long

Table 16.

Summary of mean slopes for all 13 experiments.

	long		short	
Group	Present	absent	Present	absent
		2 pixel (Large loop)		
PP [4]	32.75 (9.7)	66.09 (8.7)	59.54 (8.7)	108.43 (3.5)
non-PP [5]	27.42 (4.5)	73.43 (1.0)	57.11 (4.5)	115.15 (3.8)
letter [6]	18.80 (3.1)	37.19 (1.4)	50.75 (4.9)	39.14 (4.2)
non-letter [7]	8..04 (8.7)	50.08 (2.0)	54.35 (9.5)	89.66 (4.4)
		2 pixel (Small loop)		
line [1]	27.72 (6.3)	39.73 (3.1)	26.41 (6.6)	76.98 (2.8)
letter [10]	11.19 ((6.6)	19.21 (6.6)	44.55 (2.8)	29.31 (6.6)
non-letter [11]	13.60 (2.4)	34.15 (1.0)	52.66 (11.8)	86.04 (10.1)
		3 pixel (Small loop)		
line [2]	9.52 (3.1)	12.96 (1.0)	15.63 (3.1)	41.32 (1.4)
letter [8]	10.79 (5.2)	19.95 (3.1)	55.12 (5.9)	55.67 (7.3)
non-letter [9]	8.37 (2.1)	21.58 (0.7)	32.12 (6.6)	80.01 (1.0)

table continues

Group	long		short	
	Present	absent	Present	absent
		4 pixel		
line[3]	6.00 (2.1)	13.08 (1.0)	12.48 (2.4)	27.38 (1.4)
letter [12]	8.26 (3.1)	9.07 (2.4)	29.41 (8.3)	41.37 (1.7)
non-letter [13]	4.14 (0.7)	9.82 (1.0)	27.26 (5.9)	73.90 (1.4)

Note. Values in parentheses represent error percentage. Numbers in brackets indicate experiments.

Table 17.

Summary of significance levels for slope differences in all 13 experiments.

	Condition		
Group	Long target	Short target	Asymmetry
	2 pixel (Large loop)		
PP [4]	.0002	.0001	.0001
non-PP [5]	.0003	.0005	.0004
letter [6]	.0124	.1262	.0006
non-letter [7]	.0285	.0270	.0002
	2 pixel (Small loop)		
line [1]	.1234	.0040	.8270
letter [10]	.0781	.0236	.0002
non-letter [11]	.0060	.0136	.0019
	3 pixel (Small loop)		
line [2]	.2068	.0008	.1390
letter [8]	.0939	.9634	.0002
non-letter [9]	.0277	.0038	.0002

table continues

	Condition		
Group	Long target	Short target	Asymmetry
	4 pixel		
line[3]	.0031	.0538	.0250
letter [12]	.7917	.1424	.0020
non-letter [13]	.0740	.0007	.0032

Note. Values represent probability levels obtained from separate planned comparisons using a linear contrast of array sizes (1, 0, -1) over the two trial conditions (1, -1). Values enclosed in brackets indicate experiment numbers.

Table 18.

Comparisons of slope ratios for the six letter and non-letter experiments.

Group	Ratio	
	Long target	Short target
	2 pixel	
letter	1 : 1.70	1 : 0.66
non-letter	1 : 1.85	1 : 1.63
	3 pixel	
letter	1 : 1.85	1 : 1.01
non-letter	1 : 2.58	1 : 2.49
	4 pixel	
letter	1 : 1.09	1 : 1.41
non-letter	1 : 2.37	1 : 2.71

Note. The ratios are present versus absent. The three letter experiments were Experiments 8, 10, and 12. The three non-letter experiments were Experiments 9, 11, and 13. The loop sizes were small in all six experiments.

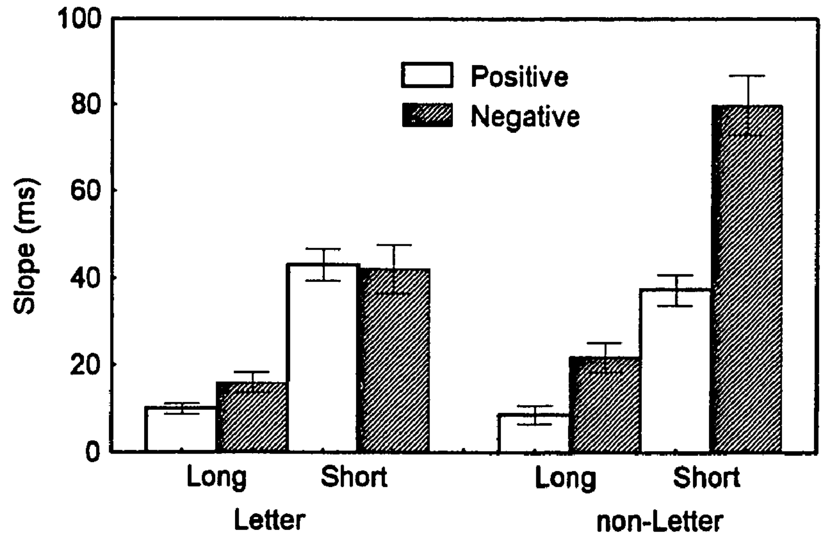

Figure 32. Comparisons of slopes (mean ± SE) of the positive and the negative trials for the long and the short target conditions. The data are the mean values of three letter experiments (Experiments 8, 10, and 12), and three non-letter experiments (Experiments 9, 11, and 13)..

target conditions as it is in the short target conditions.[31] The context difference is much larger in the short target conditions.

The hypothesis that the size of differential search rates between the target-present trials and the target-absent trials should be smaller in the letter arrays than in non-letter arrays was confirmed across all search conditions (see Table 18). In fact, in all 6 ratios of the letter arrays that used small loops (see Table 18), search rate differences between the positive and the negative trials are not significant (in Table 17) except for one (pixel 2, short target) and in this case the ratio was opposite to expectations in that negative trials were searched more rapidly than were positive trials. This is also the only condition where non-letter array has less than 1 : 2 ratio (1 : 1.63). The non-letter array's high error rates (11.8 % for positive, 10.1 % for negative trials) indicated that subjects, for some reason, might have aborted the search prematurely for both trial conditions.

Therefore, it seems to be a fair summary of the data to conclude that negative trials are indeed not much more difficult than the positive trials in the letter arrays, but are appreciably more difficult in the non-letter arrays (see Figure 31). Thus, the hypothesis in its relative terms was confirmed. It is relative since the prediction could only be made against the slowest search rate, that of exhaustive search; the search in the negative trials of the letter array should not need to be exhaustive since the negative trials do not

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[31] To follow the results of significance tests in the statistical comparisons across experiments the inferred rates are, on average, 1 : 1 for both target conditions in the letter arrays, and 1 : 2.5 and 1 : 2.1 for the long and the short target conditions, respectively, in the non-letter arrays.

consist of all the same items. One of the lines in negative trials, the line of the "p" among the "b" distractors, is different. Because the "p" is a familiar stimuli, the line in the "p" is no longer separate and independent of the influence of the loop feature as it is in the case of "non-p" and "non-b." Exactly in what manner and mechanism, the "p" line is different from "b" lines can not be specified. If the difference in the line of the "p" and "b" for negative trials, whatever the nature of that difference may be, is as large as the difference in line lengths of the "p" and "b" for positive trials, then the search rate of the negative trials would be similar to that of the positive trials. If the difference is not as large, then the search speed in the negative trials would be slower than that of the positive trials, however, it would never be as slow as that of exhaustive search. And that was the basis to predict the search patterns for the "pb" arrays in relation to those of the "non-pb" arrays since the searches in the negative trials of the "non-pb" arrays were assumed to be exhaustive.[8]

How the effect of loops on line feature maps would be computed in terms of pooled activation might be an interesting problem, but it is not at all clear how the principles of pooled activation could be translated computationally outside the typical configuration of the long or short target condition.

In contrast to the patterns for letter arrays, the negative trials in the non-letter arrays were processed as if they all consisted of the same items. Even though they have a single "non-p" among "non-b" distractors, just as in letter arrays, in terms of line features all items could be considered the same because the lines were not affected by the presence of the loops. The search task required subjects to compare this unaffected line feature map's activation as it does in line array tasks.

Because "pb" arrays are, at least on the surface, obviously different from the line arrays, and nevertheless the theoretical arguments put forward in the present thesis are based on the processing of line features, it becomes important to consider whether the data can be explained by other factors. The following sections discuss such possibilities in relation to each set of experiments.

Line Experiments

There are two unexpected results in the line experiments. One is the lack of clear asymmetry in positive trials between the long and the short target conditions and the other is that the ratios between positive and negative search rates in the long target conditions which were less than 1 : 2 ratio.

As single experiments (see Table 17), the asymmetry of the positive trials[32], was absent in Experiment 1 (a difference of 2 pixels); present but not statistically significant in Experiment 2 (a difference of 3 pixels); and significant in Experiment 3 (a difference of 4 pixels). In the statistical comparisons across experiments, there was no interaction between the asymmetry and the level of discriminability; all three groups did not show

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[32] The asymmetry should be more important in positive trials than in negative trials. By definition, search rates of negative trials are dependent on positive trials. This is because groupings of items, i.e., the optimal level of cluster size, should operate for the purpose of finding the target. The slow search rate of negative trials are supposed to be due to the fact that all clusters have to be examined.

the asymmetry. However, the absence seems to be due to the strong effect in the lowest discriminability level. The asymmetry effects of Experiment 2 (9.52 ms versus 15.63 ms) and Experiment 3 (6 ms versus 12.48 ms) may not have been large enough to override its absence in Experiment 1 (27.72 ms versus 26.41 ms) in the between group analyses. Therefore, the most reasonable conclusion is that for the lines the asymmetry reliably appears only when the discriminability level is high enough between target and distractor line features. If the discriminability is moderate or low, the asymmetry effect weakens or disappears altogether.

Treisman's model does predict that if target-distractor discriminability becomes too low, the asymmetry may not be observed. If the difference between the target line and distractor lines is too small, the activation levels of negative trials of the long and short conditions would be similar to each other, and accordingly the advantage of the long target conditions will not be large enough to show the asymmetry.

To recapitulate, in experimental settings that produce the asymmetry, the size of the difference between activations of the positive and the negative trials is the same in both the long and the short target conditions. The advantage of the long target condition solely comes from the fact that its activation level in negative trials is weaker than that in the negative trials of short target condition. The same size difference against the weaker standard will make the distinction between the positive and the negative trials easier in the long target than in the short target conditions. If the discriminability is too low, the activation levels of the negative trials in both conditions, and thus, their Weber fractions, would be similar, which will result in the absence of the asymmetry. In accordance, as discriminability got higher, the slopes became faster and the size of the asymmetry got bigger (see Figure 8).

However, a careful reading of Treisman's model reveals peculiar contradictions that could not predict her data patterns. The model's elaborate search machinery that generates the asymmetry hinges on one crucial assumption: The visual system keeps track of the display size of the positive and the negative instances. In this pooled response model, it is not the detection of a target per se that determines response and response speed. A comparison of two pooled responses (from positive and negative instances) is the basis of such responses.[33] For example, in the long target condition, the system compares pooled responses from a positive trial of array size 6 and a negative trial of array size 6, and decides the higher activation has the target; the less does not. As the array size increases, the difference between the "more" and the "less" becomes unreliable because the total amount of activation itself increases. The advantage of the long target condition is that the difference between the "more" and the "less" always is measured against the lesser amount of activation (its negative trials) than that in the short target condition (its negative trials). If the system loses its ability to automatically determine display sizes, then the responses for the positive and the negative trials will no

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[33] Strictly speaking, the comparison does not seem to be for individual trials, but merely a basis for Weber fraction. Depending on the size of Weber fraction, the system decides the number of subgroups to employ, which in turn determines the search speed. However, to reach the Weber fraction, the matching of equal display sizes is crucial.

longer be accurate because sometimes a larger array size of target-absent will generate more activation than a smaller array size of target-present. The advantage of the long target can not be maintained either because the same size difference may no longer be reliably compared with the stronger background distractors in the short target conditions. How reasonable an assumption it is that the visual system can somehow automatically match the display sizes (at least until the criterion of Weber fraction can be set up) in an experimental setting that uses mixed array sizes could be an open question, but it seems extremely unlikely.[34]

There is also an issue of the pooling process in relation to trial conditions. In Treisman's model, the mechanism that distinguishes positive trials from negative ones based on the pooled activation does not seem to be fully developed yet. For instance, the easiest way to configure such a mechanism would be to have the system set up a response criterion. If the accumulation of activation reaches the criterion within a given amount of time, the system decides that the target is in the array, if not, it is absent. Obviously, such machinery would not generate a search time difference between the positive and the negative trials because the amount of waiting time the system spends for the accumulation to reach (for positive trials) or not reach (for negative trials) the criterion is equal.

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[34] For example, a hypothetical experiment that uses 10 or 20 different array sizes (instead of several) in the same block of trials can be imagined. Whether the visual system can keep track of 20 different array sizes to compute Weber fraction has not been tested.

Conversely, the system can compare the times the accumulation reaches the criterion. The larger the accumulation is, the faster it will reach the criterion. If the accumulation time is brief, then the array is judged to have the target; if it takes longer, then it is judged not to contain the target. Because response execution is supposed to occur when the accumulation reaches the criterion, this will make response to positive trials faster than the one to negative trials. However, for such a mechanism to work, two criteria (one for positive trials and another for negative trials) are needed as the total amount of accumulation is different in the positive and the negative trials. This defeats the purpose of measuring accumulation time, because the criterion for the negative trials should be lower than the one for the positive trials. For the less amount of accumulation to reach the lower criterion may take similar time as that for the more accumulation to reach the higher criterion.

Moreover, both mechanisms (measuring the accumulation level or measuring the time to reach the criterion) predict the converse data pattern of the long target condition in the short target condition. In other words, in the short target condition, the negative trials should be faster than the positive ones, since in the short target condition the accumulation level of the negative trials is "more" and the one of the positive trials is "less."

The resolution of those theoretical problems would be an issue of its own that requires a different set of experiments.

A more problematic result for the thesis' hypotheses is the small difference between the positive and the negative trials in the long target conditions. Since the pattern was repeated in two different experiments, Experiments 1 and 2, with different discriminability (pixels 2 and 3) and with different subjects, it can not be easily dismissed.

Two situations could be imagined where the search rates for the positive and the negative trials are similar. First, if the target is so conspicuous and salient, subjects could assume that an absence of such a salient item guarantees the target's absence and abort the search in negative trials. If subjects do not equate the absence of a salient item with the absence of the target, they would continue the search in the negative trials and this will lead to the ratio (positive to negative) close to 1 : 2. To infer such a strategy from data patterns, the positive trials should be fast. In fact, the line experiments of pixel difference 3 and 4 could have been such situations. In these two experiments, the search rates were fast enough (under 10 ms) to apply such logic. However, in the experiment of pixel difference of 2, search rates are rather slow (27.72 ms for target-present) indicating that the target was not salient.

The second situation where search rates for target-present and target-absent instances are expected to be similar is when subjects employ "exhaustive search" not only in negative trials but also in positive trials. In other words, they do not stop the search even when the target was found. Although such a counter-intuitive search method was used in one of Sternberg's experiments (1966), there is no reason to assume it in the line experiment with pixel difference 2. In fact, the slow search times imply attended processing, clearly associated with self termination.

Thus, the most likely reason seems to be 'premature termination' of search. The subjects did not employ "exhaustive search" in negative trials. They aborted the search before they were certain that the target was absent. The higher error rates in the positive trials than in the negative trials support such inference.

With the lack of clear asymmetry in positive trials, and the less than 1 : 2 ratios in the long target condition, Experiment 1 does not conform to the data patterns of the rest of the experiments. To decide whether this is a particularly anomalous pattern or if it genuinely has something to do with the low discriminability level, a replication of the results should be attempted in the future occasion.

pp and non-pp

Experiments 4 and 5 examined target search with arrays where the same loops were added to all the lines in Experiment 1. The addition completely changed the data pattern from that of Experiment 1. The search times for the long target, when it was present, remained similar to that of the line arrays, but the negative trials took twice as long. In addition, the short target search was now much more difficult than the long target search (see Table 16). Thus, the asymmetry of the positive trials that was not observed in the line experiment with the same discriminability (2 pixels) was in fact very strong in both "pp" and "non-pp" arrays.

The results of these experiments included increased overall RT with the same data patterns across search conditions (1 : 2 ratio and asymmetry) as those of line array, and confirmed the prediction of the hypothesis for non-letter arrays.

As pointed out earlier, there are two important aspects of the added loops in these two experiments. First, the loops were "constant" with exactly the same loops added to all the lines in the display. Second, the presence of the loops was irrelevant to the experimental task with target status based solely on a difference in line length. Given that the additional features were constant and irrelevant, the system overhead resources dealing with the loop features should influence all conditions uniformly. Therefore, the prediction was a uniform change of the results in Experiment 1. Although, the data can not be compared with anomalous results of Experiment 1, the patterns are similar to those of Experiments 2 (3 pixel) and 3 (4 pixel).

The obtained results would be expected when the line maps were separate and were not affected by the loop features in any direct way. Thus, the "non-pp" data are assumed to be based on the line feature maps' activation just as they were in the line arrays. Two plausible hypotheses could refute such arguments.

First, the slope difference between the positive and the negative trials could be the result of conjunction search. Subjects could have been involved in a conjunction search in its strictest manner. They may have focused their attention on each item, conjoined the features according to location indices, matched the result against the target item in memory, then gone on to the next item, and this process would continue until the target was found. The long reaction times, steep slopes, and 1 : 2 ratios, the factors that are usually interpreted as evidence of conjunction search (Treisman & Gelade, 1980), make this argument reasonable.

If this were the case, the serial search in the current experiment would be due to efforts to conjoin the features and not to any difference of distractor activation levels or processing cost for loop features. But all prior relevant work attests to the fact that when feature level information is sufficient for response selection, subjects evidently do not wait till the system progresses to the next processing stage. None of the current tasks require conjunction search, tasks can be accomplished by comparing the activation levels of line feature map. Moreover, conjunction search does not predict the asymmetry which is so compelling here. In a strict item by item serial search of conjunctions, the difference of the distractor activation level should not matter because the search is no longer based on the pooled activation.

A second argument that the search data are not the product of line feature maps' activation is that something other than the line feature was used as a basis for the target search.[35] The addition of the loop might have created an emergent feature, for example, a descender, in the display. Although there is a perfect correlation between the line length

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[35] Because there is difference between the conditions of the familiar and unfamiliar contexts, the argument does not necessarily refute the claim that contexts bring on changes at a feature level. However, it would weaken the position put forward here, namely, the very same features that were used in both contexts are changed depending on the level of familiarity.

and the size of the descender, the level of discriminability for descenders might be different, even with the same physical line length. In other words, unlike the case of the line feature, "more" of descender may have been sufficiently more than "less" to produce the asymmetry. If the lack of asymmetry in the 2 pixel line experiment was due to a low level of discriminability, then the presumed higher level of discriminability of the descender feature could create the asymmetry.

Not only the overall speed of reaction time is too slow for the change of discriminability level[36], the invalidity of the above account is apparent when the "pb" and "non-pb" data are also examined. In those conditions, the target items always have descenders. If a descender feature is used to detect the target, both the long and the short target conditions are reduced to the same condition of discriminating small descender from large descender; distractors do not matter since they do not have descenders (they have ascenders). Therefore there should not be any difference between the two conditions; the observed asymmetry of "pp" conditions should not exist in "pb" conditions. In fact, the asymmetry is very strong. If a descender feature is not used in "pb" conditions, which would benefit greatly had it been used, there is no reason to believe that the feature is used in "pp" where the only benefit is its assumed higher discriminability.

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[36] Slope values for "pp" and "non-pp" arrays are larger than that of the line array (Experiment 1). If the discriminability has increased, overall slopes should have decreased accordingly.

Thus, neither the conjunction argument nor the emergent feature argument could adequately explain the data.

There was no difference between search patterns in "pp" and "non-pp" arrays. It seems the effect of loop features on lines is the same, whether the context in which they are grouped is familiar or not. However, the differential effects of familiarity associated with the added loops on line features can not necessarily be tested with the "pp" and "non-pp" arrays. Since all the lines in letter "p"s could be equally affected in the same manner and by a comparable magnitude, the difference between the target and the distractor items would be likely to be the same as that of unaffected lines in "non-pp" arrays. For a more definitive examination of familiarity effects, a line in "p" needs to be examined against a line that is affected in a different manner in a similarly familiar context, which is a condition of "pb" array.

pb and non-pb

The patterns of results were consistent in all experiments. In non-letter conditions, the negative always were slower than the positive trials, with slope ratios for positive versus negative responses mostly larger than 1 : 2 ratio. In contrast, for the letter conditions negative trials were not significantly different from positive trials, particularly in the short target conditions (see Table 18).

In analyses of single experiments, the long target conditions of the letter and non-letter arrays showed different levels of significance. The differences between the rates of target search in the positive and the negative trials of the letter arrays were not statistically significant (12 ms versus 20 ms, 11 ms versus 20 ms, 8 ms versus 9 ms for the 2 pixel difference, 3 pixel difference and 4 pixel difference conditions, respectively). However, they were significantly different in the non-letter arrays (14 ms versus 35 ms, 8 ms versus 22 ms, 4 ms versus 10 ms, for the 2 pixel difference, 3 pixel difference and 4 pixel difference conditions, respectively).

This pattern, that is, the lack of clear differences between the positive and the negative trials in the letter arrays, and its distinct presence in the non-letter arrays became even more accentuated in the short target conditions. The letter arrays generated slopes of 45 ms (positive) versus 30 ms (negative), and the non-letter arrays 53 ms (positive) versus 94 ms (negative), in the 2 pixel conditions. The slopes for the positive and the negative trials in the letter arrays were both 55 ms when the level of discriminability was a moderate size of 3 pixels, but the slopes in the non-letter arrays were very different from each other (32 ms versus 80 ms). When the level of discriminability was very high (4 pixels), the positive trials were searched at similar speeds in both the letter and the non-letter arrays, but the negative trials were searched much more slowly for the non-letter arrays (29 ms versus 41 ms for the letters; 27 ms versus 74 ms for the non-letters).

These various differences between the discriminability levels were apparently not stable enough to be significant in the statistical comparisons across experiments. Instead, a strong and clear difference between the letter arrays and the non-letter arrays appeared. There was no difference between the positive and the negative trials in the letter arrays, either in the long or the short target conditions, although overall the short target trials were slower than the long target trials (an average difference of 43 ms versus 13 ms). The negative trials were always slower than the positive trials for the non-letters, both in the long (an average difference of 9 ms versus 22 ms) and the short target conditions (an average difference of 37 ms versus 80 ms). As in the letter arrays, the long target trials were more difficult than the short target trials.

In summary, the data suggest that the effect of the discriminability in the letter and the non-letter arrays is inconclusive in the current experimental settings. At least at a descriptive level, the very highly discriminable items seem to be processed differently from the low or the moderately discriminable ones. For instance, the letter arrays show steeper slopes for the negative trials than for the positive trials in the long target conditions if the level of discriminability is low, but the slope difference disappears if the items are highly discriminable (see Table 16).

There is a consistent and significant difference between the letter and the non-letter arrays. For the letter arrays, the search rates for negative trials are not different from the positive trials, but they are for the non-letter arrays. Thus the data show that the line in "p" is processed quite differently from both the line in "b" and the line in "non-p."

The change in the array configuration from "pp" to "pb" might seem to have added new relational features, such as "ascender" or "the position of the loop," that can make the target item distinct from distractors. As a consequence, it is possible that responses were no longer a reflection of the line feature maps' activation levels. In order to support the argument that the loop changed the perceptual nature of the target line but the new factors that might have been created by the loop did not cause the search time difference, other plausible explanations should be eliminated as follows.

At first glance, the strategy used for "pb" arrays seems obvious: (a) find "p"; (b) if the "p" is longer/shorter than distractors then press one button; (c) if the "p" is the same length as distractors then press the other button.[37] If the decision time for comparing the target's length to that of distractors is assumed to be the same whether it is relatively longer or shorter, then the search time should be the same for both positive and negative trials.

This two-step process assumes implicitly a rather unproved point, i.e., that the "p" is processed as a separate feature from its stem length. To assume that when subjects find the "p" in step (a) its line length does not affect the search time is to assume that "p" and its component line are separate features. If "p" is represented as a whole and not a collection of parts that need to assembled, and the ability to achieve this level of representation is a function of familiarity, then the lack of difference between trial conditions for "pb" arrays becomes more explicable. If "p" is an integrated unit, it is clearly a different visual object from "b," in which case, detection of "p" among "b"s should not be affected by whether its line length is shorter or longer than the lines in "b"s. It is a different object as a circle is different from a triangle.

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[37] Interestingly enough, this is the strategy subjects often said they used.

However, all the "pb" experiments of this thesis refute such assumption. If "p" is a separate feature, the data should have been very different from those obtained. For instance, all "pb" search arrays contained the "p," therefore the search task should have been a matter of finding the feature "p." This makes all search conditions in all arrays equivalent, and accordingly there should not have been search time differences. [38] Furthermore, the "p" should have "popped-out" in any kind of array because it was a unique feature. In contrast the overall search speed in all search conditions in the current experiments is too slow to argue for unitized "p" and "b."

One can perhaps assume that it is not the global "p" but the loop location on the top that subjects search for in the first step; they find "the loop on top" first and then decide its line length. However, an attribute of "loop on top" describes the "non-pb" conditions too. If finding the "loop on top" and then deciding its line length is a more optimal search strategy than finding the line length difference alone, the same strategy should be equally optimal in "non-pb" conditions. But in "non-pb" conditions, search in the negative trials invariably took more than twice as long as the positive ones. Furthermore, if "loop on top" is assumed to be a feature of its own, separate from the lines, then just in the example of "ascender/descender" that was introduced in the "pp" discussion, the search condition does not predict the asymmetry. If "loop on top," a unique feature in the array

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[38] Notice that any argument that involves line length, such as, "p" and "b" are more similar in the same line length condition (negative trials) than they are in the different length condition (positive trials), brings the difference of "p" and "b" back to the line feature level.

(since distractors have "loop on bottom"), can be detected without being influenced by line length, which is the critical assumption of this argument, there is no reason for a decision making of "the shorter line" (in the short target condition) should take longer time than that of "the longer line" (in the long target condition). In other words, both the long and the short target conditions are reduced to the same comparison of "loop on top" with a longer line versus "loop on top" with a shorter line. Since it's the same kind of comparison in both target conditions, there is no reason to expect that one search should be more difficult than the other. In fact, any argument that does not utilize line feature maps at the first step of the search can not predict the asymmetry between the long and the short target conditions.

The completely different data patterns for the "pb" and "non-pb" arrays can not be attributed simply to a usage of different feature maps in the two search tasks, whatever those feature may be, because "pp" and "non-pp" experiments showed the same patterns of results. When the added loop could not help to find the target, as in the "pp" (because the target was the same "p" as distractors) and the "non-pp" experiments, "pp" and "non-pp" data looked exactly the same, even though "pp" was a letter array and "non-pp" was a non-letter array. The same data pattern can only mean that regardless of the items' familiarity, the same feature maps were used for target searches both in "pp" and "non-pp." In other words, the difference between the "pp" and the "non-pp" is equivalent to the difference between the "pb" and the "non-pb" in that the "non-pb" is a horizontally displaced loop version of the "pb" just as the "non-pp" is of the "pp." If the same feature maps were used in the "pp" and "non-pp" tasks, there is no basis to argue for the different (and unknown) feature maps in the "pb" and the "non-pb" tasks.

Even if there might have been emergent relevant features that were different in "pb" arrays and "non-pb" arrays, what they could be independent of familiarity is not clear. Although the nature of the task in the "pb" experiments may seem to be considerably changed from that of the line experiment, the only difference between the target-present and the target-absent trials is still the same "more or less" of the vertical line length. Therefore, these unknown emergent features, if they exist, have to be perfectly correlated with, and yet separate entities from line length, while still producing the differential effect between the letter and the non-letter experiments. Such an emergent feature then clearly has some association with "letterness" in the letter group. If an emergent feature in the letter group is not independent from its "letterness," then it only helps the argument that letters are qualitatively different from non-letters at the level of feature analysis, although it may weaken the argument for the line feature's change per se.

The most logical inference from all the results then would be that the changes in data patterns were associated with the difference between "p" and "b" in the letter arrays and "non-p" and "non-b" in the non-letter arrays. The line in the "p" and the line in the "b" are processed differently than the line in "non-p" and the line in "non-b." In terms of physical differences in line segments, all of these conditions were exactly the same in the sense that the only factor that differentiated the target from the distractors and the long targets from the short targets was the different line lengths.

This pattern of slope changes indicated that there may be an interaction of dimensions in search tasks depending upon the context of the stimuli used in the task. Even when all other component features other than the target dimension itself are the same, the target dimension's activation level could be affected by the existence of other features if the context was familiar. What kind of interaction it was and precisely in what fashion the interaction affected the performance needs further study.

The implication of the present study is that the interaction influenced by familiarity existed at the feature level. The existence of possible interaction at the feature level might seem to blur the distinction between features and conjunctions. After all, features are features because they are separate components of an eventual conjunction, and once the interaction between features is allowed to result in phenomenological "compounds," then the basic construct of a feature becomes ambiguous. On the other hand, the idea that exactly the same line feature map registers a line in all its varieties is counter-intuitive also. The human visual system perceives not just a line but its variations. To perceive the variations then different feature maps have to be added for the eventual representation of real world visual objects in the visual system. To register a visual scene is not to register only its bare, abstracted overall structures. Eventually all the details and variations have to be encoded. Juggling around the limited number of feature detectors that registered the same percept in all its varieties will never be able to handle the richness of real world visual scenes.

Allowing features to maintain their elemental status, and at the same time to permit them to be influenced by other features might be a better solution. It may be the same line feature that encodes a vertical line in "p" and in "non-p." But its activation patterns appear to be influenced by other features, and this influence appears to be greater within a familiar compared to a novel context.

Invariance of features across various visual scenes is at the heart of feature extraction models of pattern perception. However, the current experiments show that a feature in one context may change its nature or its perceptual meaning in the presence of other features, even when the other features are constant and irrelevant to the task. Therefore, the present findings suggest that the assumption that the visual system initially extracts separate, isolated features as independent entities from visual scenes might need to be reexamined.

Appendix A

Notes

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[a] In template matching theory, a pattern is recognized by comparing directly information from the visual stimuli to previously stored holistic patterns, which were encoded in their entirety. The letter "A" is recognized when the encoded image matches best with the "A" template among all others in long term memory. This family of models is considered inadequate as a theory of human pattern recognition primarily because it requires an unmanageably huge number of templates. Any object transformed from its standard shape by alternations in size, orientation or position will fail to match the appropriate template. Consequently, in order to recognize the letter "A" a system would have to store every template of every possible instance of "A."

[b] For instance, if creation of new features is possible, not only does the visual system need to handle an unmanageable number of features, as in template models, but by definition, features created in one context need to be applied universally in all visual scenes. In other words, if a "A" feature was created by way of repeated exposure and experience, the feature "A" ought to be utilized as one of many features in visual processings for objects that have nothing to do with letter or word contexts. Whether features created in a particular context, like "A," if it is possible, could take on a nature primitive and elemental enough, as that of a line detector, to be applied in all context is doubtful.

[c] "Integral dimensions" in Garner's framework might be equivalent to "features" in Treisman's model. For example, color may always be processed as a single feature, and not as a conjunction of hue, brightness and saturation. Treisman herself at first suggested the two constructs as a measure of convergence validity of both theories in early vision (Treisman & Souther, 1985). However, this line of work was never pursued further apparently due to the theoretical changes within Garnerian camps (Shepp, 1989; Smith & Kemler-Nelson, 1984; Smith & Evans, 1989). In theories of dimensional structure of visual objects, the dichotomy between integral and separable dimensions gradually developed to a continuum, only extreme ends of which are exclusively integral or separable.

Viewed from the perspective of Treisman's model, experiments in dimensionality always deal with conjunctions. This is so because a stimulus is a single visual object, such as a color patch or a triangle of different sizes. As such, the stimulus' components always reside within the area of a focused attention, and therefore are conjoined together. The task in such experiments is to classify the stimulus according to a target feature's value, for instance, degree of brightness. The task then is equivalent to dissemble features from the conjunction and the experiments' measures are as to whether the features could be dissembled and if so how easily (see section of integral/separable dimensions in literature review).

[d] This master activation map maintains only the summed final totals of each activation and does not preserve information for the separate sources; each item has now combined activation of the two modules, color and orientation.

It is not clear where in this model the location information operates. Unlike Treisman's model which generates a master location map separately from the other features, Wolfe's model seems to, even though it is never explicitly stated, put the location information directly in each feature map. In other words, each feature map has some sort of topographical information of visual scene, and the final activation map is just a sum of such module's activation patterns. In such mechanisms therefore, the concept of attention in the feature-integration model as a binding agent of features (i.e., attention moves from one location to another on the location map, integrating relevant features at each location) would not be viable any more.

[e] As the noise parameter is varied, slopes for conjunction searches can vary from parallel to serial. A search for a triple conjunction ($O_{big, red}$) among distractors that shared one feature with the target ($X_{small, red}$, $O_{small, green}$ and $X_{big, green}$) generated a parallel slope (0.4 ms). The same target, when the distractors shared two features with the target ($X_{big, red}$, $O_{big, green}$ and $O_{small, red}$) thereby making the search as equivalent to Treisman's conjunction search (the target was different from distractors by one feature) generated much steeper slope (4.5 ms). The search for the same $O_{big,red}$ among $X_{big,red}$ and $O_{big, green}$ (in other words, the target was O_{red} and the distractors were X_{red} and O_{green}) obtained the similar speed (5.2 ms). In the first case, the target has three sources of top-down activation whereas the distractors have only one. The large total activation of the target presumably overrode any system noise. In the second and the third cases, distractors have two sources of top-down activation. Therefore, the target's advantage is only one more source of activation which makes the misdirection of attention more likely than the first case (Wolfe, Cave, & Franzel, 1989).

[f] The concept of "word features" may be related to theories of "word superiority" (Reicher, 1969). Word superiority, the phenomenon where a detection of a letter in a word is more accurate than that of the letter in isolation, indicates that word identification can occur independent of and perhaps before letter identification. A system that identifies words separately from letters would need "word features" (unless it has templates for all words). However, the "visual" nature of such features are often called into question (Smith, Lott, & Cronnel, 1969; Colhart & Freeman, 1974) since words can

be easily identified with some practice even when they are presented with no delimiting boundaries (e.g., delimitingboundaries) or in alternate cases (e.g., AlTeRnAtInGcAsEs). The most successful models for the word superiority (McClelland & Rumelhart, 1981; Paap, Newsome, McDonald, & Schvaneveldt, 1982) in fact posit that letter identification is prior to word identification. In such hierarchical network models, a higher level word node is connected to its component letter nodes at the lower level. The architecture of such models is that excitation of letter nodes is directly fed into word nodes without any time delay. The system does not wait until the letter nodes reach their maximum level of excitation, upon which identification of the letters is achieved, and then begin the activation of word level nodes. Rather, before the letters are identified their node at the word level is already activated to a considerable extent. By varying parameters, such as the activation levels that letters and words have to reach for identification, the summed amount of activation of word nodes versus that of letter nodes, the hierarchical network models can explain the word superiority. But such models do not seem to be concerned with mechanisms of feature detectors. Although letters are presented as collection of features, for all practical purposes, they are treated as holistic percepts and the primary interest is in the interaction of such letter units and their composite words, rather than in letter features and word features.

[8] Although the nature of the difference between the lines of "p" and "b" in the negative trials (in other words, the lines of equal length) can not defined at the current stage, a tentative account can be constructed for the different data patterns between the long and the short target conditions. Since to find a longer line among shorter lines is easy, the line length difference in the positive trials could be larger than the unknown difference in the lines of the "p" and "b" of the negative trials. Therefore, the search speed would be slower for the negative trials than for the positive trials. To find a shorter line among longer lines is difficult, which is the condition of the positive trials in the short target condition. And the difference between the lines of "p" and "b," in this case, may be as large as that of the positive trials. The difference then will yield similar search slopes for the positive and the negative trials.

This account, however, contradicts one fundamental component of Treisman's Pooled response model (Treisman & Gormican, 1988). That is, in the model, the longer line is easy to detect not because it is long but because the negative trials for the long target condition consist of shorter lines. Unlike the model, for the above argument to work, the long line should be easy to detect because it is longer than other items in arrays since there is no negative trial of the shorter lines of the same length. In this context, the negative trials have a different line in "p" and all the same lines in "b."

Appendix B

Tables of Statistical Analyses

General Notes

- Values enclosed in parentheses represent mean square errors.
- *S* indicates subjects.
- *n* indicates the number of subjects.
- Target (L) consists of "long" and "short" conditions.
- Trial (P) consists of "present" and "absent" conditions.
- Array (A) sizes are one, six and twelve items.
- Pixel (G) consists of two, three and four pixel differences between the target item and distractor items in line lengths.

Analyses Tables of Experiment 1 (line, 2 pixel difference)

Table B1.

Analysis of Variance for Experiment 1.

Source	*df*	*F*
Target (L)	1	3.66
L × *S* within-group error	7	(60529.91)
Trial (P)	1	19.16**
P × *S* within-group error	7	(50413.61)
Array (A)	2	76.48**
A × *S* within-group error	14	(23202.43)
L × P	1	1.48
L × P × *S* within-group error	7	(24104.68)
L × A	2	14.23**
L × A × *S* within-group error	14	(6977.72)
P × A	2	9.91**
P × A × *S* within-group error	14	(24249.10)
L × P × A	2	7.66**
L × P × A × *S* within-group error	14	(13919.04)

Note. ***p* < .01.

Table B2.

Standard Deviation for Each Condition in Experiment 1.

	Array size		
	1	6	12
		Long target	
Present	133.6	133.7	212.6
Absent	165.0	265.2	347.4
		Short target	
Present	206.4	134.3	145.4
Absent	105.4	290.4	413.9

Table B3.

Planned comparisons for each target condition and asymmetry in experiment 1.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	4.13	14.97**	.05
Error	7	(9336.94)	(40927.10)	(8805.65)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{**}p < .01$.

Analyses Tables of Experiment 2 (line, 3 pixel difference)

Table B4.

Analysis of Variance for Experiment 2.

Source	df	F
Target (L)	1	7.15*
L × *S* within-group error	7	(45524.60)
Trial (P)	1	22.63**
P × *S* within-group error	7	(15778.77)
Array (A)	2	43.23**
A × *S* within-group error	14	(8861.69)
L × P	1	3.08
L × P × *S* within-group error	7	(4602.52)
L × A	2	18.51**
L × A × *S* within-group error	14	(3986.40)
P × A	2	20.97**
P × A × *S* within-group error	14	(2476.65)
L × P × A	2	13.67**
L × P × A × *S* within-group error	14	(2202.29)

Note. $*p < .05$. $**p < .01$.

Table B5.

Standard Deviation for Each Condition in Experiment 2.

	Array size		
	1	6	12
		Long target	
Present	95.9	115.3	101.2
Absent	128.3	133.4	132.9
		Short target	
Present	179.2	124.2	182.2
Absent	103.2	154.9	229.1

Table B6.

Planned comparisons for each target condition and asymmetry in experiment 2.

Source	*df*		*F*	
		Long target	Short target	Asymmetry
Effect	1	1.93	31.11**	2.79
Error	7	(1440.91)	(5092.30)	(3125.29)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry. $**p < .01$.

Analyses Tables of Experiment 3 (line, 4 pixel difference)

Table B7.

Analysis of Variance for Experiment 3.

Source	*df*	*F*
Target (L)	1	5.22
L × *S* within-group error	7	(16302.71)
Trial (P)	1	28.41**
P × *S* within-group error	7	(7667.45)
Array (A)	2	23.32**
A × *S* within-group error	14	(9040.98)
L × P	1	4.20
L × P × *S* within-group error	7	(4422.06)
L × A	2	7.40**
L × A × *S* within-group error	14	(3833.36)
P × A	2	5.64*
P × A × *S* within-group error	14	(5254.52)
L × P × A	2	2.89
L × P × A × *S* within-group error	14	(3400.79)

Note. *$p < .05$. **$p < .01$.

Table B8.

Standard Deviation for Each Condition in Experiment 3.

	Array size		
	1	6	12
		Long target	
Present	96.8	115.1	107.8
Absent	97.0	109.9	138.2
		Short target	
Present	73.8	139.8	130.0
Absent	103.4	155.1	279.7

Table B9.

Planned comparisons for each target condition and asymmetry in experiment 3.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	19.43**	5.36	8.07*
Error	7	(683.57)	(9752.85)	(1302.50)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

*$p < .05$. **$p < .01$.

Table B10.

Planned comparisons of trial conditions over array size with the long and the short target conditions collapsed together in Experiment 3.

Source	*df*	*F*
Effect	1	9.81*
Error	7	(6024.30)

Note. Linear coefficients used were 1, 0, -1 for array sizes; 1, -1 for trial conditions; and 1, 1 for target conditions. The two trial conditions were present and absent.

*$p < .05$.

Analyses Tables of Experiment 4 (PP, 2 pixel difference)

Table B11.

Analysis of Variance for Experiment 4.

Source	*df*	*F*
Target (L)	1	46.34**
L × *S* within-group error	7	(26789.40)
Trial (P)	1	170.78**
P × *S* within-group error	7	(12191.89)
Array (A)	2	342.29**
A × *S* within-group error	14	(12918.76)
L × P	1	1.08
L × P × *S* within-group error	7	(22572.26)
L × A	2	29.56**
L × A × *S* within-group error	14	(10250.99)
P × A	2	32.37**
P × A × *S* within-group error	14	(12682.08)
L × P × A	2	3.98*
L × P × A × *S* within-group error	14	(4654.91)

Note. *$p < .05$. **$p < .01$.

Table B12.

Standard Deviation for Each Condition in Experiment 4.

	Array size		
	1	6	12
		Long target	
Present	91.22	113.62	100.46
Absent	122.57	282.85	244.00
		Short target	
Present	79.48	161.10	109.94
Absent	76.14	134.06	122.10

Table B13.

Planned comparisons for each target condition and asymmetry in experiment 4.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	46.94**	136.29**	84.00**
Error	7	(5782.40)	(4197.40)	(2161.30)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{**}p < .01$.

Analyses Tables of Experiment 5 (non-PP, 2 pixel difference)

Table B14.

Analysis of Variance for Experiment 5.

Source	*df*	*F*
Target (L)	1	54.15**
L × *S* within-group error	7	(34559.96)
Trial (P)	1	44.85**
P × *S* within-group error	7	(59339.82)
Array (A)	2	121.97**
A × *S* within-group error	14	(38243.60)
L × P	1	4.39
L × P × *S* within-group error	7	(24968.38)
L × A	2	18.50**
L × A × *S* within-group error	14	(20192.60)
P × A	2	30.34**
P × A × *S* within-group error	14	(21234.06)
L × P × A	2	.92
L × P × A × *S* within-group error	14	(9016.50)

Note. ***p* < .01.

Table B15.

Standard Deviation for Each Condition in Experiment 5.

	Array size		
	1	6	12
		Long target	
Present	117.9	157.2	265.9
Absent	80.5	259.1	412.7
		Short target	
Present	75.3	223.6	165.4
Absent	141.4	393.7	400.1

Table B16.

Planned comparisons for each target condition and asymmetry in experiment 5.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	43.05**	35.44**	40.12**
Error	7	(11958.3)	(22147.4)	(6018.1)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{**}p < .01$.

Table B17.

Planned comparisons of trial conditions over array size with the long and the short target conditions collapsed together in Experiment 5.

Source	*df*	*F*
Effect	1	56.75**
Error	7	(22653.00)

Note. Linear coefficients used were 1, 0, -1 for array sizes; 1, -1 for trial conditions; and 1, 1 for target conditions. The two trial conditions were present and absent.

$^{**}p < .01$.

Analyses Tables of Experiment 6 (letter, 2 pixel difference, large loop)

Table B18.

Analysis of Variance for Experiment 6.

Source	*df*	*F*
Target (L)	1	23.91**
L × *S* within-group error	7	(18195.22)
Trial (P)	1	3.30
P × *S* within-group error	7	(11133.47)
Array (A)	2	50.88**
A × *S* within-group error	14	(25554.00)
L × P	1	29.33**
L × P × *S* within-group error	7	(8164.00)
L × A	2	11.40**
L × A × *S* within-group error	14	(6293.55)
P × A	2	1.64
P × A × *S* within-group error	14	(8943.40)
L × P × A	2	6.88**
L × P × A × *S* within-group error	14	(8385.14)

Note. $^{**}p < .01$.

Table B19.

Standard Deviation for Each Condition in Experiment 6.

	Array size		
	1	6	12
		Long target	
Present	80.1	108.8	125.3
Absent	91.1	126.0	282.2
		Short target	
Present	84.1	147.1	248.3
Absent	91.0	224.6	254.3

Table B20.

Planned comparisons for each target condition and asymmetry in experiment 6.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	11.15*	3.01	35.89**
Error	7	(7192.88)	(11889.37)	(7028.1)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{*}p < .05$. $^{**}p < .01$.

Analyses Tables of Experiment 7 (non-letter, 2 pixel difference, large loop)

Table B21.

Analysis of Variance for Experiment 7.

Source	*df*	*F*
Target (L)	1	24.29**
L × *S* within-group error	7	(72977.80)
Trial (P)	1	15.48**
P × *S* within-group error	7	(111948.20)
Array (A)	2	45.58**
A × *S* within-group error	14	(50132.80)
L × P	1	2.27
L × P × *S* within-group error	7	(23760.30)
L × A	2	41.34**
L × A × *S* within-group error	14	(9926.50)
P × A	2	11.73**
P × A × *S* within-group error	14	(29360.00)
L × P × A	2	0.13
L × P × A × *S* within-group error	14	(22049.20)

Note. ***p* < .01.

Table B22.

Standard Deviation for Each Condition in Experiment 7.

	Array size		
	1	6	12
		Long target	
Present	218.4	153.1	151.8
Absent	138.4	275.8	472.4
		Short target	
Present	95.5	236.8	206.6
Absent	170.5	334.9	311.9

Table B23.

Planned comparisons for each target condition and asymmetry in experiment 7.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	9.44*	8.35*	75.36**
Error	7	(41539.4)	(32665.7)	(6159.5)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$*p < .05$. $**p < .01$.

Table B24.

Planned comparisons of trial conditions over array size with the long and the short target conditions collapsed together in Experiment 7.

Source	*df*	*F*
Effect	1	12.95*
Error	7	(50935.50)

Note. Values enclosed in parentheses represent mean square errors. Linear coefficients used were 1, 0, -1 for array sizes; 1, -1 for trial conditions; and 1, 1 for target conditions. The two trial conditions were present and absent.

$^{*}p < .05$.

Analyses Tables of Experiment 8 (letter, 3 pixel difference)

Table B25.

Analysis of Variance for Experiment 8.

Source	*df*	*F*
Target (L)	1	28.38**
L × *S* within-group error	7	(45085.18)
Trial (P)	1	3.38
P × *S* within-group error	7	(55674.91)
Array (A)	2	39.35**
A × *S* within-group error	14	(30897.24)
L × P	1	0.64
L × P × *S* within-group error	7	(45408.00)
L × A	2	25.44**
L × A × *S* within-group error	14	(15318.57)
P × A	2	.32
P × A × *S* within-group error	14	(20676.82)
L × P × A	2	.28
L × P × A × *S* within-group error	14	(18270.13)

Note. ***p* < .01.

Table B26.

Standard Deviation for Each Condition in Experiment 8.

	Array size		
	1	6	12
		Long target	
Present	79.3	76.2	146.7
Absent	66.0	205.6	178.0
		Short target	
Present	69.7	136.4	214.4
Absent	112.4	281.4	561.3

Table B27.

Planned comparisons for each target condition and asymmetry in experiment 8.

Source	*df*		*F*	
		Long target	Short target	Asymmetry
Effect	1	3.75	.002	56.28**
Error	7	(5428.88)	(57010.34)	(8378.4)

Note. Each *F* is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

*$p < .05$. **$p < .01$.

Analyses Tables of Experiment 9 (non-letter, 3 pixel difference)

Table B28.

Analysis of Variance for Experiment 9.

Source	*df*	*F*
Target (L)	1	48.22**
L × *S* within-group error	7	(45383.64)
Trial (P)	1	44.14**
P × *S* within-group error	7	(25220.54)
Array (A)	2	46.23**
A × *S* within-group error	14	(27985.81)
L × P	1	12.55**
L × P × *S* within-group error	7	(11525.61)
L × A	2	40.86**
L × A × *S* within-group error	14	(11051.40)
P × A	2	18.53**
P × A × *S* within-group error	14	(12260.28)
L × P × A	2	7.68**
L × P × A × *S* within-group error	14	(9506.32)

Note. ***p* < .01.

Table B29.

Standard Deviation for Each Condition in Experiment 9.

	Array size		
	1	6	12
		Long target	
Present	56.3	90.7	119.0
Absent	70.1	145.9	209.7
		Short target	
Present	80.6	190.4	148.7
Absent	113.5	255.3	422.7

Table B30.

Planned comparisons for each target condition and asymmetry in experiment 9.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	7.67*	18.01**	61.12**
Error	7	(5588.46)	(30912.0)	(2367.7)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^*p < .05$. $^{**}p < .01$.

Analyses Tables of Experiment 10 (letter, 2 pixel difference, small loop)

Table B31.

Analysis of Variance for Experiment 10.

Source	*df*	*F*
Target (L)	1	30.65**
L × *S* within-group error	7	(8940.16)
Trial (P)	1	1.58
P × *S* within-group error	7	(6625.89)
Array (A)	2	88.98**
A × *S* within-group error	14	(7553.00)
L × P	1	38.54**
L × P × *S* within-group error	7	(3233.26)
L × A	2	34.69**
L × A × *S* within-group error	14	(3304.17)
P × A	2	.99
P × A × *S* within-group error	14	(4383.22)
L × P × A	2	7.11**
L × P × A × *S* within-group error	14	(4652.09)

Note. ***p* < .01.

Table B32.

Standard Deviation for Each Condition in Experiment 10.

	Array size		
	1	6	12
	Long target		
Present	95.2	81.7	80.4
Absent	37.4	103.0	98.9
	Short target		
Present	51.7	108.6	128.6
Absent	48.9	91.1	114.9

Table B33.

Planned comparisons for each target condition and asymmetry in experiment 10.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	4.53	8.30*	60.07**
Error	7	(3289.06)	(6817.08)	(4472.3)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

*$p < .05$. **$p < .01$.

Analyses Tables of Experiment 11 (non-letter, 2 pixel difference, small loop)

Table B34.

Analysis of Variance for Experiment 11.

Source	*df*	*F*
Target (L)	1	20.40**
L × *S* within-group error	7	(94365.40)
Trial (P)	1	55.38**
P × *S* within-group error	7	(20770.52)
Array (A)	2	102.12**
A × *S* within-group error	14	(21963.41)
L × P	1	2.10
L × P × *S* within-group error	7	(22159.86)
L × A	2	24.10**
L × A × *S* within-group error	14	(22726.68)
P × A	2	12.54**
P × A × *S* within-group error	14	(14960.46)
L × P × A	2	1.08
L × P × A × *S* within-group error	14	(9242.97)

Note. $^{**}p < .01$.

Table B35.

Standard Deviation for Each Condition in Experiment 11.

	Array size		
	1	6	12
	Long target		
Present	108.6	165.8	246.9
Absent	162.7	304.2	258.5
	Short target		
Present	105.4	231.9	133.3
Absent	101.0	159.2	272.8

Table B36.

Planned comparisons for each target condition and asymmetry in experiment 11.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	15.15**	10.73*	23.37**
Error	7	(6973.7)	(25686.0)	(16377.2)

Note. Each *F* is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$*p < .05$. $**p < .01$.

Table B37.

Planned comparisons of trial conditions over array size with the long and the short target conditions collapsed together in Experiment 11.

Source	*df*	*F*
Effect	1	14.36**
Error	7	(25168.10)

Note. Linear coefficients used were 1, 0, -1 for array sizes; 1, -1 for trial conditions; and 1, 1 for target conditions. The two trial conditions were present and absent.

$^{**}p < .01$.

Analyses Tables of Experiment 12 (letter, 4 pixel difference)

Table B38.

Analysis of Variance for Experiment 12.

Source	*df*	*F*
Target (L)	1	45.06**
L × *S* within-group error	7	(16133.05)
Trial (P)	1	33.07**
P × *S* within-group error	7	(8403.88)
Array (A)	2	52.24**
A × *S* within-group error	14	(9579.58)
L × P	1	.78
L × P × *S* within-group error	7	(28952.15)
L × A	2	66.16**
L × A × *S* within-group error	14	(2682.44)
P × A	2	2.44
P × A × *S* within-group error	14	(4127.20)
L × P × A	2	1.32
L × P × A × *S* within-group error	14	(6940.76)

Note. ***p* < .01.

Table B39.

Standard Deviation for Each Condition in Experiment 12.

	Array size		
	1	6	12
		Long target	
Present	33.8	34.7	28.7
Absent	40.0	139.1	111.5
		Short target	
Present	32.0	134.3	150.4
Absent	56.8	127.3	180.1

Table B40.

Planned comparisons for each target condition and asymmetry in experiment 12.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	.08	2.73	23.01**
Error	7	(3155.38)	(12491.35)	(4862.5)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{**}p < .01$.

Analyses Tables of Experiment 13 (non-letter, 4 pixel difference)

Table B41.

Analysis of Variance for Experiment 13.

Source	*df*	*F*
Target (L)	1	42.06**
L × *S* within-group error	7	(63759.43)
Trial (P)	1	48.42**
P × *S* within-group error	7	(20537.69)
Array (A)	2	25.28**
A × *S* within-group error	14	(31866.61)
L × P	1	22.43**
L × P × *S* within-group error	7	(15916.96)
L × A	2	21.86**
L × A × *S* within-group error	14	(21427.51)
P × A	2	21.51**
P × A × *S* within-group error	14	(7732.93)
L × P × A	2	26.44**
L × P × A × *S* within-group error	14	(3856.14)

Note. ***p* < .01.

Table B42.

Standard Deviation for Each Condition in Experiment 13.

	Array size		
	1	6	12
		Long target	
Present	92.9	77.9	82.7
Absent	78.9	87.4	146.6
		Short target	
Present	75.3	159.3	207.7
Absent	108.2	248.8	478.6

Table B43.

Planned comparisons for each target condition and asymmetry in experiment 13.

Source	*df*	*F*		
		Long target	Short target	Asymmetry
Effect	1	4.41	33.78**	19.19**
Error	7	(1780.35)	(15647.5)	(6884.6)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1). The two trial conditions are positive and negative in the long and the short target conditions, and positive trials of both target conditions for the asymmetry.

$^{**}p < .01$.

Linearity of Slope Values

Table B44.

Percentage of sums of squares for array size that is due to linearity in each slope (line length differences of two pixels).

Group		SS effect	SS linear	linear %
		Long target		
line	Present	373313.3	373122.2	99.95%
	Absent	841436.6	789485.6	93.83%
		Short target		
	Present	338506.2	337240.1	99.63%
	Absent	2888595	2848180.	98.60%
		Long target		
letter	Present	73459.07	63514.08	86.46%
	Absent	180662.5	180344.6	99.82%
		Short target		
	Present	972170	970246.2	99.80%
	Absent	422034.7	420686.8	99.68%

table continues

Group		SS effect	SS linear	linear %
		Long target		
non-letter	Present	91021.1	90601.00	99.54%
	Absent	598141.1	578740.6	96.76%
		Short target		
	Present	1456296	1382976.	94.97%
	Absent	3830946	3680642.	96.08%

Table B45.

Percentage of sums of squares for array size that is due to linearity in each slope (line length differences of three pixels).

Group		SS effect	SS linear	linear %
		Long target		
line	Present	44546.64	44379.74	99.63%
	Absent	81510.22	81417.2	99.89%
		Short target		
	Present	119038.1	117405.1	98.63%
	Absent	832763.3	820029.4	98.47%
		Long target		
letter	Present	57791.87	57247.02	99.06%
	Absent	194947.8	194584.7	99.81%
		Short target		
	Present	1476087	1465051	99.25%
	Absent	1505180	1504218	99.94%

table continues

Group		SS effect	SS linear	linear %
		Long target		
non-letter	Present	34417.69	34316.73	99.71%
	Absent	229969.4	228560.7	99.39%
		Short target		
	Present	599718	523054	87.22%
	Absent	3227172	3162804	98.01%

Table B46.

Percentage of sums of squares for array size that is due to linearity in each slope (line length differences of four pixels).

Group		SS effect	SS linear	linear %
		Long target		
line	Present	18517.75	16965.06	91.62%
	Absent	93671.59	85995.56	91.81%
		Short target		
	Present	75767.25	75762.56	99.99%
	Absent	369243.6	358202.3	97.01%
		Long target		
letter	Present	34619.4	33739.26	97.46%
	Absent	52638.3	42223.26	80.21%
		Short target		
	Present	454777.4	431314	94.84%
	Absent	852330.3	842582.2	98.86%

table continues

Group		SS effect	SS linear	linear %
		Long target		
non-letter	Present	9384.75	7965.563	84.88%
	Absent	47551.58	46010.25	96.76%
		Short target		
	Present	365286.6	363910.6	99.62%
	Absent	2662366	2661792	99.98%

Tables of Statistical Comparisons across Experiments

Line Experiments

Table B47.

Analsis of Variance of all effects in line experiments.

Source	*df*	*F*
Between subjects		
Group (G)	2	10.31**
S Within-group error	21	(228584.4)
Within subjects		
Target (L)	1	14.52**
L × G	2	.49
L× *S* Within-group error	21	(40785.7)
Trial (P)	1	56.74**
P × G	2	2.93
P × *S* Within-group error	21	(24619.9)
Array (A)	2	141.16**
A × G	4	15.85**
A × *S* Within-group error	42	(13701.7)
L × P	1	5.96*
L × P × G	2	.12
L × P × *S* Within-group error	21	(11043.1)

table continues

Source	*df*	*F*
L × A	2	37.75**
L × A × G	4	1.55
L × A × *S* Within-group error	42	(4932.5)
P × A	2	24.59**
P × A × G	4	2.80*
P × A × *S* Within-group error	42	(10660.1)
L × P × A	2	17.00**
L × P × A × G	4	2.76*
L × P × A × *S* Within-group error	42	(6507.4)

Note. $*p < .05$. $**p < .01$.

Table B48.

Analysis of Variance for long target conditions in all three line experiments.

Source	*df*	*F*
Pixel (G)	2	9.25**
S within-group error	21	(118798.2)
Trial (P)	1	31.57**
P × *S* within-group error	21	(13562.3)
Array (A)	2	81.11**
A × *S* within-group error	42	(6083.7)
G × P	2	2.06
P × *S* within-group error	21	(13562.3)
G × A	4	15.37**
A × *S* within-group error	42	(6083.7)
P × A	2	7.69**
P × A × *S* within-group error	42	(4175.1)
G × P × A	4	1.67
P × A × *S* within-group error	42	(4175.1)

Note. **p* < .05. ***p* < .01.

Table B49.

Analysis of Variance for short target conditions in all three line experiments.

Source	*df*	*F*
Pixel (G)	2	8.48**
S within-group error	21	(150572.0)
Trial (P)	1	46.82**
P × *S* within-group error	21	(22100.8)
Array (A)	2	129.62**
A × *S* within-group error	42	(12550.5)
G × P	2	2.05
P × *S* within-group error	21	(22100.8)
G × A	4	10.46**
A × *S* within-group error	42	(12550.5)
P × A	2	26.22**
P × A × *S* within-group error	42	(12992.3)
G × P × A	4	3.15*
P × A × *S* within-group error	42	(12992.3)

Note. $*p < .05$. $**p < .01$.

Table B50.

Analysis of Variance for positive trials in the long and the short target conditions in all three line experiments.

Source	*df*	*F*
Pixel (G)	2	10.94**
S within-group error	21	(73337.95)
Trial (P)	1	5.33*
P × *S* within-group error	21	(24666.54)
Array (A)	2	63.20**
A × *S* within-group error	42	(6115.22)
G × P	2	.44
P × *S* within-group error	21	(24666.54)
G × A	4	7.14**
A × *S* within-group error	42	(6115.22)
P × A	2	1.45
P × A × *S* within-group error	42	(3590.70)
G × P × A	4	.81
P × A × *S* within-group error	42	(3590.70)

Note. $*p < .05$. $**p < .01$.

Table B51.

Planned comparisons of trial conditions in the three line experiments.

Source	*df*	*F*	
		Long target	Asymmetry
Effect	1	11.59**	2.30
Error	21	(3820.48)	(4411.15)

Note. Each F is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1) with three pixel conditions collapsed (1, 1, 1). The two trial conditions are positive and negative in the long target conditions, and positive trials of both target conditions for the asymmetry.

$*p < .05$. $**p < .01$.

Letter Experiments

Table B52.

Analsis of Variance of all effects in letter experiments.

Source	*df*	*F*
Between subjects		
Group (G)	2	3.04
S Within-group error	21	(114014.7)
Within subjects		
Target (L)	1	89.60**
L × G	2	3.96*
L × *S* Within-group error	21	(23386.1)
Trial (P)	1	10.42**
P × G	2	4.90*
P × *S* Within-group error	21	(23568.2)
Array (A)	2	142.80**
A × G	4	3.19*
A × *S* Within-group error	42	(16009.9)
L × P	1	1.79
L × P × G	2	2.51
L × P × *S* Within-group error	21	(25864.5)

table continuse

Source	df	F
L × A	2	89.24**
L × A × G	4	3.38*
L × A × S Within-group error	42	(7101.7)
P × A	2	.49
P × A × G	4	.83
P × A × S Within-group error	42	(9729.1)
L × P × A	2	.87
L × P × A × G	4	1.94
L × P × A × S Within-group error	42	(9954.3)

Note. $*p < .05$. $**p < .01$.

Table B53.

Analysis of Variance for long target conditions in all three letter experiments.

Source	*df*	*F*
Pixel (G)	2	4.65*
S within-group error	21	(38573.14)
Trial (P)	1	46.31**
P × *S* within-group error	21	(5456.53)
Array (A)	2	51.97**
A × *S* within-group error	42	(5025.94)
G × P	2	2.94
P × *S* within-group error	21	(5456.53)
G × A	4	1.50
A × *S* within-group error	42	(5025.94)
P × A	2	2.60
P × A × *S* within-group error	42	(5034.99)
G × P × A	4	.76
P × A × *S* within-group error	42	(5034.99)

Note. $*p < .05$. $**p < .01$.

Table B54.

Analysis of Variance for short target conditions in all three letter experiments.

Source	*df*	*F*
Pixel (G)	2	2.63
S within-group error	21	(98827.66)
Trial (P)	1	.89
P × S within-group error	21	(43976.16)
Array (A)	2	147.01**
A × S within-group error	42	(18085.73)
G × P	2	3.74*
P × S within-group error	21	(43976.16)
G × A	4	3.73*
A × S within-group error	42	(18085.73)
P × A	2	.02
P × A × S within-group error	42	(14648.42)
G × P × A	4	1.61
P × A × S within-group error	42	(14648.42)

Note. $*p < .05$. $**p < .01$.

Table B55.

Analysis of Variance for positive trials in the long and the short target conditions in all three letter experiments.

Source	df	F
Pixel (G)	2	9.06**
S within-group error	21	(33866.12)
Trial (P)	1	143.32**
P × *S* within-group error	21	(9646.10)
Array (A)	2	155.48**
A × *S* within-group error	42	(6699.84)
G × P	2	4.92*
P × *S* within-group error	21	(9646.10)
G × A	4	4.33**
A × *S* within-group error	42	(6699.84)
P × A	2	78.15**
P × A × *S* within-group error	42	(5058.57)
G × P × A	4	3.90**
P × A × *S* within-group error	42	(5058.57)

Note. **p* < .05. ***p* < .01.

Non-Letter Experiments

Table B56.

Analsis of Variance of all effects in non-letter experiments.

Source	*df*	*F*
Between subjects		
Group (G)	2	2.85
S Within-group error	21	(207000.6)
Within subjects		
Target (L)	1	99.70**
L × G	2	.24
L × *S* Within-group error	21	(67836.2)
Trial (P)	1	146.77**
P × G	2	.07
P × *S* Within-group error	21	(22176.3)
Array (A)	2	151.44**
A × G	4	3.89**
A × *S* Within-group error	42	(27271.9)
L × P	1	28.74**
L × P × G	2	2.22
L × P × *S* Within-group error	21	(16534.1)

table continues

Source	*df*	*F*
L × A	2	79.06**
L × A × G	4	.35
L × A × *S* Within-group error	42	(18401.9)
P × A	2	49.24**
P × A × G	4	.32
P × A × *S* Within-group error	42	(11651.2)
L × P × A	2	21.01**
L × P × A × G	4	1.77
L × P × A × *S* Within-group error	42	(7535.1)

Note. $*p < .05$. $**p < .01$.

Table B57.

Analysis of Variance for long target conditions in all three non-letter experiments.

Source	*df*	*F*
Pixel (G)	2	3.47*
S within-group error	21	(114470.0)
Trial (P)	1	70.39**
P × *S* within-group error	21	(8828.1)
Array (A)	2	45.09**
A × *S* within-group error	42	(7638.8)
G × P	2	3.00
P × *S* within-group error	21	(8828.1)
G × A	4	5.16**
A × *S* within-group error	42	(7638.8)
P × A	2	17.14**
P × A × *S* within-group error	42	(3847.6)
G × P × A	4	2.07
P × A × *S* within-group error	42	(3847.6)

Note. *$p < .05$. **$p < .01$.

Table B58.

Analysis of Variance of the long target conditions of all three non-letter experiments with the three discriminability level collapsed.

Source	*df*	*F*
Trial (P)	1	60.00**
P × *S* Within-group error	23	(10360.39)
Array (A)	2	33.10**
A × *S* Within-group	46	(10404.71)
T × A	2	15.68**
T × A × *S* Within-group error	46	(4206.88)

Note. **p* < .05. ***p* < .01.

Table B59.

Analysis of Variance for short target conditions in all three non-letter experiments.

Source	*df*	*F*
Pixel (G)	2	1.30
S within-group error	21	(160366.7)
Trial (P)	1	104.02**
P × *S* within-group error	21	(29882.3)
Array (A)	2	137.78**
A × *S* within-group error	42	(38035.0)
G × P	2	.39
P × *S* within-group error	21	(29882.3)
G × A	4	1.92
A × *S* within-group error	42	(38035.0)
P × A	2	43.42**
P × A × *S* within-group error	42	(15338.8)
G × P × A	4	.59
P × A × *S* within-group error	42	(15338.8)

Note. **p* < .05. ***p* < .01.

Table B60.

Analysis of Variance of the short target conditions of all three non-letter experiments with the three discriminability level collapsed.

Source	*df*	*F*
Trial (P)	1	109.82**
P × *S* Within-group error	23	(28304.79)
Array (A)	2	127.54**
A × *S* Within-group	46	(41088.47)
T × A	2	45.03**
T × A × *S* Within-group error	46	(14790.49)

Note. *$p < .05$. **$p < .01$.

Table B61.

Planned comparisons of trial conditions in all three non-letter experiments.

Source	*df*	*F*	
		Long target	Short target
Effect	1	23.01**	57.14**
Error	23	(5581.3)	(23293.0)

Note. Each *F* is computed separately using linear coefficients for array sizes (1, 0, -1) and two trial conditions (1, -1) with three pixel conditions collapsed (1, 1, 1). The two trial conditions are present and absent.

*$p < .05$. **$p < .01$.

Table B62.

Analysis of Variance for positive trials in the long and the short target conditions in all three non-letter experiments.

Source	*df*	*F*
Pixel (G)	2	3.51*
S within-group error	21	(76274.21)
Trial (P)	1	113.28**
P × *S* within-group error	21	(16123.90)
Array (A)	2	112.53**
A × *S* within-group error	42	(7263.00)
G × P	2	.1344
P × *S* within-group error	21	(16123.90)
G × A	4	6.62**
A × *S* within-group error	42	(7263.00)
P × A	2	42.07**
P × A × *S* within-group error	42	(8048.78)
G × P × A	4	1.62
P × A × *S* within-group error	42	(8048.78)

Note. *$p < .05$. **$p < .01$.

Table B63.

Subject characteristics of all experiments that used small loops.

Pixel	*n* (Male)	*n* (Female)	Age Mean	Age SD	Age Range
		Line experiments			
2	5	3	19.38	1.06	18-21
3	2	6	24.13	9.72	17-45
4	2	6	27.50	8.02	22-45
		Letter experiments			
2	3	5	30.00	10.04	18-40
3	1	7	20.38	2.07	18-24
4	1	7	30.75	14.22	16-50
		Non-letter experiments			
2	4	4	23.88	6.17	18-34
3	0	8	20.38	3.16	18-27
4	2	6	31.75	7.25	18-40

Table B64.

Subject characteristics of all experiments that used large loops and two pixel differences in line lengths.

Experiment	*n* (Male)	*n* (Female)	Age Mean	Age SD	Age Range
PP	3	5	20	3.56	17-28
non-PP	2	6	18.88	1.64	17-21
letter	1	7	20.38	2.26	18-25
non-letter	5	2	19.86	1.68	18-22

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