

INVESTIGATING THE ROLES OF FEATURES AND PRIMING IN VISUAL SEARCH

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INVESTIGATING THE ROLES OF FEATURES AND PRIMING IN VISUAL SEARCH

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SUMMARY

Identifying and locating specific objects amidst irrelevant, distracting items can be difficult when one is unsure of where, or even what, to look for. Priming the perceptual/cognitive system for specific features or objects is one way of helping observers to locate and identify target items (e.g., Grice & Gwynne, 1985; Laarni and Hakkinen, 1994).

Past research has demonstrated that priming single features does indeed affect search performance (e.g., Hailston & Davis, 2006; Huang & Pashler, 2005). But, what happens when more than one feature is primed? Does priming two features result in better performance than priming only one? What about three features? How does feature priming compare to simply priming the entire object itself?

The current research addressed these questions with a series of three visual search experiments. In the first experiment performance in simple feature search was compared against triple-conjunction search performance. Three prominent models of visual search were compared to see which best predicted actual performance. In the second and third experiments the effects of multiple feature priming on search accuracy were examined in a triple-conjunction search (Experiment 2) and a whole-object search (Experiment 3). Moreover, in Experiment 3 the effectiveness of whole-object primes were compared to multiple-features primes.

Results show that none of the three models can accurately predict performance in all cases, suggesting some modification of each is necessary. Furthermore, valid primes resulted in performance benefits, and these benefits increased with the number of primed

features. Finally, no performance costs of invalid priming were observed in the current experiments.

CHAPTER I

INTRODUCTION

Visual search is the act of looking for something. People perform visual search tasks every day. These tasks range in difficulty from very efficient (e.g., locating your coffee pot for a morning cup of coffee) to very inefficient (e.g., locating that elusive parking spot at the local shopping mall during the holiday season). It is important to recognize that these tasks are often complicated by the fact that individual objects do not exist in isolation. Nor do individual features of a given object exist in isolation. Identifying and locating specific objects amidst other irrelevant, distracting items can be difficult when one is unsure of where or even what to look for. Priming the perceptual/cognitive system for specific features or objects is one way of helping observers to find target items (e.g., Grice & Gwynne, 1985; Laarni and Hakkinen, 1994).

The experiments reported here examined performance in triple conjunction visual search tasks. Targets and distractors in triple conjunction search are defined by three features. Furthermore, each distractor shares at least one of the same feature values (e.g., color) with the target item. The first experiment compared three prominent, contemporary models of visual attention (Eckstein, Thomas, Palmer, & Shimozaki, 2000; Lavie, 1995; Wolfe, 1995) to see which best predicts performance in a triple-conjunction visual search with only one possible target. The second experiment examined the effects of priming multiple feature dimensions on both identifying and locating targets in a triple conjunction visual search. The third experiment examined priming effects in a whole-object visual search task.

Human Visual Feature Processing

We do not perceive our visual environment as simply a collection of individual features. Rather, our environment consists of many different, complex objects. Successfully navigating through and interacting with our environment requires us to recognize and localize these objects. For example, when searching for our car in a crowded parking lot, we do not look for the round feature of the wheels, the curved shape of the windshield, or the symmetry between the left and right sides of the vehicle. We have a representation of what the specific vehicle looks like and search for that specific object. Similarly, when walking down a crowded street we do not view obstacles in our path as a group of random features, but rather as whole objects (e.g., a crowd of people).

At least in early processing, however, the human visual system does view the world as individual features. Thus, to understand how attention operates in visual search it makes sense to begin at the level of individual features. For this reason, much of the previous visual search research has focused on features (e.g., Eckstein et al, 2000; Huang & Pashler, 2005; Palmer, 1995; Treisman & Gelade, 1980; Wolfe, 1994)

In human visual processing information is carried from the level of the retina up through the system via two major pathways. These pathways are referred to as the magnocellular (M-pathway) and the parvocellular (P-pathway) (Livingstone & Hubel, 1988). (For other organizational models see Lennie, 1998; Ungerleider & Mishkin, 1982.) The two pathways carry markedly different information and, for a while, were believed to operate independently of each another (Livingstone & Hubel, 1988).

Although more recent evidence suggests that the two pathways do communicate with

each other (e.g., Constantine-Paton, Cline, & Debski, 1990), the notion persists that they carry predominantly different types of information.

The M-pathway originates with large ganglion cells in the eye – in fact, *magno* means large. These cells have receptive fields that are larger than their counterparts in the P-pathway. Cells in the M-pathway are achromatic, but very sensitive to both contrast and motion. Conversely, cells in the P-pathway are color sensitive and do not respond well to motion. Both the M-pathway and P-pathway ganglion cells project to the lateral geniculate nucleus (LGN) of the thalamus.

The LGN is a layered structure, and each of its six layers receives information from only one of the two pathways. Layers 1 and 2 receive information from the M-pathway cells whereas layers 3 to 6 receive information from the P-pathway cells.

The separation of information continues past the level of the LGN to area V1 in the primary visual cortex, where it remains largely segregated. Color and orientation information continue to travel along the P-pathway but, even in the initial stages of cortical processing, the cells that process them are distinct.

Color is processed by cells called parvo-blob cells. These parvo-blobs are color selective cells that have no orientation preferences. Parvo-blob cells pass their information to the thin stripes of area V2 (De Valois & De Valois, 1990).

Orientation information is processed by cells called the parvo-interblob cells. These interblob cells respond best to lines of a particular orientation, but are insensitive to direction of movement. Most lack color selectivity, but can respond to luminance-based contrast borders. Some inter-blob cells are end-stopped cells that respond either to short

or long lines or edges. The parvo-interblob cells project their information to the pale stripes of V2 (De Valois & De Valois, 1990).

So, we see that although both color and orientation information is carried along the P-pathway, the information is processed largely independently from one another, once this information reaches the cortex.

Information in both M- and P-pathways undergoes several different stages of processing. Ultimately, the information in the M-pathway projects to the medial temporal area (area MT) and from there to the parietal cortex. Cells in area MT are highly sensitive to motion information, and can be especially informative for *where* something is. Information from the P-pathway is projected to area V4 and to the temporal cortex. Cells in area V4 are highly sensitive to color, whereas, cells in the temporal cortex are sensitive to form and detail (e.g., orientation) – both can be especially informative for *what* something is (De Valois & De Valois, 1990).

Thus, one can argue that motion is processed along a perceptually distinct pathway (the M-pathway) from either color or orientation. Furthermore, one can argue that orientation is processed distinctly from color information, even though both travel along the P-pathway. In making this claim, however, it is important to realize that even if features are processed by different regions of the brain or by different pathways, they are not necessarily completely independent. That is, these different brain regions and pathways can communicate with one another. Still, to the extent that these features are processed by different types of neurons and, in the case of motion, by a different pathway, we can consider them to be *perceptually distinct*. That is, the human can perceive motion, color, or orientation relatively independently of each other.

We can further this argument by examining known perceptual deficits and noticing how they do not seem to share any relationship with one another. For example, individuals who suffer from color deficiencies (e.g., red/green color deficiency) rarely have any difficulty in detecting motion or even recognizing objects. Similarly, individuals who suffer from akinetopsia have little difficulty describing static objects in detail. This argument can not be made with regard to all visual features. For example, one can not argue that spatial frequency is processed even quasi-independently of color, orientation, or motion.

Spatial frequency information is carried along both the M- and P-pathways. The same cells that process color, orientation, and motion information also process spatial frequency information. The cells that process motion in the M-pathway also process lower spatial frequencies, while in the P-pathway the inter-blob cells are tuned to higher spatial frequencies and the blob-cells are tuned to intermediate spatial frequencies (Graham, 1989). Thus, while we can differentiate the structures largely responsible for processing color, orientation, and motion, we can not effectively dissociate those cells that process spatial frequency information from those that process the three other features (De Valois & De Valois, 1990).

I was interested in investigating the effects of priming multiple features in these experiments. For the reasons discussed above, I chose to examine color, orientation, and motion. Spatial frequency was beyond the scope of the current study because it is not perceptually distinct from the other features of interest.

Theories of Attention in Visual Search

Many contemporary models of visual search (e.g., Bundensen, 1990; Eckstein, et al., 2000; Lavie, 2005, Logan, 1996, Treisman & Gelade, 1980; Wolfe, 1994) discuss visual processing at the level of component features. These models discuss methods of improving search performance (e.g., increasing search accuracy) in terms of either target enhancement, distractor inhibition, or both. They vary with regard to the nature and role of attention in visual search, the roles of user-initiated top-down processes vs. stimulus-driven bottom-up processes, and how attention is distributed across a visual scene.

I examined three prominent models of visual search and tested the predictions of each about performance in a triple conjunction search (Experiment 1). The three models I compared are Lavie's Perceptual Load Theory (Lavie, 1995), Wolfe's Guided Search (e.g., Wolfe, 1994), and Eckstein's Multi-Dimensional Signal Detection Model (Eckstein et al, 2000). All three models have successfully predicted search performance accuracy in a number of conditions, but each can make qualitatively different predictions about performance in triple-conjunction search tasks where distractors share only one feature with target stimuli. These predictions were tested in Experiment 1.

Additionally, the models were conceptually expanded to try and account for priming effects in cases where distractors share one *or* two features with the target stimulus (Experiments 2 & 3).

Perceptual Load Theory

Perceptual Load Theory (PLT) assumes that the degree of an observer's perceptual load dictates the nature of attentional processing (Lavie, 1995; Lavie & Tsal, 1994). This load is the cause of performance changes in visual search. Perceptual Load Theory draws

distinctions between situations involving early and late selection of stimuli, and makes different predictions about the effects on search performance observed in each.

According to PLT, early selection is defined as situations involving the perceptual processing of stimuli (e.g., detecting a target defined by a single feature), and late selection as those involving more object-based selective attention (e.g., identifying a target among a group of irrelevant distractors). Although no clear definition of perceptual load has been given, often it is operationally defined as a function of set size and of task difficulty (Lavie, 2005). For example, in a pop-out search a target differs from a homogeneous set of distractors; this is an easy task and results in a low-load condition. But, in a conjunction search a target is defined by the conjunction of two or more features that distinguish it from any single distractor. The need to process multiple features should increase the load, making conjunction search a more difficult task. Due to the increased load we should see substantial decline in triple-conjunction search, as compared to single feature search.

Guided Search

In Guided Search (GS) all items in a visual display are first broken down into their respective feature components (Wolfe, 1994). All of these individual feature singletons are compared individually against their neighbors for local salience differences along a particular dimension (e.g., color). These local saliences are weighted and aggregated to form what Wolfe refers to as *an activation map*. The activation map is further acted upon by user-initiated top-down processes (e.g., expectations and goals): Assuming that we know what we are looking for, the target items should receive an increased weighting

over those for which we are not searching. The greater the weighting, the more likely we are to find a specific target among distracting information.

In GS when targets and distractors are defined by only one feature dimension (e.g., searching for a red target among homogeneous green distractors), the target-defining feature (in this case red) receives a heavy bottom-up weighting because it differs from all of its neighbors. This bottom-up weight is further increased by top-down processing because it matches what we are looking for (viz., a red target). Thus, in this example the red target appears to “pop-out” of the display. In these types of searches, performance is relatively stable across various set-sizes, assuming the salience difference between target and distractors is sufficiently discriminable.

In the case of triple-conjunction searches where each distractor shares only one feature with the target stimulus, even though there is more complex information in the display to process, GS predicts performance should be comparable to single-feature search performance. This is because during the initial stage of feature processing each feature dimension is processed independently of the others. Additionally, the observer’s top-down expectations and goals will further increase these salience differences in the activation map. So, once again the target appears to stand out among distractor stimuli.

According to GS, when simple feature searches are compared to triple-conjunction searches, observed set-size effects in the triple-conjunction search should *not* be substantially larger than those observed in the single feature searches. In triple conjunction search, however, if the distractor shares more than one feature with the target, then overall performance will be reduced in triple-conjunction search.

Multidimensional Signal Detection Theory Model

Models of visual attention based on Signal Detection Theory (SDT) (Green & Swets, 1966) assume that errors in performance arise due to the presence of some type of normally-distributed decision noise. This decision noise arises because the neural representations of both targets and distractors are assumed to fluctuate from trial to trial. Thus, on some trials it is possible that the internal response elicited by a distractor can exceed that elicited by a target. In terms of visual search, noise can be defined as distracting information present in the display, random firing of neurons, or the confusability between target and distracting information, which is related to the salience and strength of stimuli (e.g., Doshier & Lu, 2000; Duncan & Humphreys, 1989; Eckstein, 1998; Eckstein et al, 2000; Lu & Doshier, 2000; Palmer, 1995).

In SDT changes in search performance are often explained in terms of the observer's sensitivity (e.g., Green & Swets, 1966; MacMillan & Creelman, 2005). The more sensitive the observer is, the more likely she can discriminate between signals (target) and noise (distractors). In simple feature search when the differences within a feature dimension are highly discriminable, such as searching for the vertical bar amidst horizontal distractors, the target is easily distinguished from the distractors and performance is relatively stable (although there may be small set size effects perhaps due to the presence of decision noise) across various set sizes.

Eckstein and his colleagues (Eckstein et al, 2000) expanded the predictions and assumptions made by SDT (Green & Swets, 1966) in feature search to explain performance in triple-conjunction search. In his Multidimensional Signal Detection Model (MSDM) performance in triple-conjunction searches is predicted to be *better* than

that observed in the single-feature conditions. The reason is that in this triple-conjunction search the target differs from each distractor along two different feature dimensions.

Targets that differ from distractors along two dimensions increase the observer's chance to identify or locate it by a factor of two, as compared to cases in which targets and distractors vary along only one feature dimension (e.g., single-feature searches). Thus, when the target shares only one feature dimension with any distractor, MDSM predicts better overall performance for triple-conjunction search than in single-feature search.

Comparing Model Predictions

All three of the above models predict relatively stable performance in single-feature search tasks, when the target is very discriminable from a distractor. That is, performance should remain similar, with perhaps a very small or no set-size effect, regardless of the number of items present in the display. They do differ significantly, however, with regard to triple-conjunction search performance (see Figure 1).

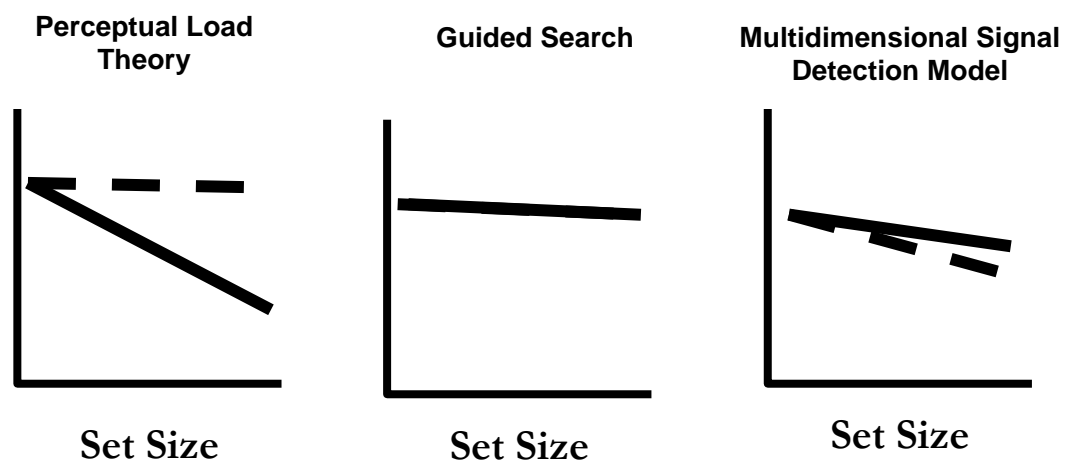


Figure 1. Illustration of qualitative predictions each of the three models makes for both simple feature searches (solid lines) and triple-conjunction searches (broken lines) in which the target shares only one feature with any given distractor. The x axis represents set size, and the y axis represents performance accuracy (higher = better). Note in the GS model the two lines overlap

Lavie's PLT (1995) predicts large set-size effects in the triple-conjunction search due to the increased perceptual load associated with the added feature dimensions. Wolfe's GS model predicts equivalent performance in both search conditions (Wolfe, Cave, & Franzel, 1989). Eckstein's MDSM (2000) predicts better performance in the triple-conjunction search because information for targets is combined across three feature dimensions, and each distractor differs from the target along two of those dimensions. In Experiment 1 the three models were pitted against one another to determine which best predicts actual performance.

Priming and Visual Search

Identifying and locating items can be difficult especially when one is uncertain of where, or even what, to look for (e.g., Davis, Shikano, Main, Hailston, & Sathian, 2006).

Several suggestions for reducing this uncertainty have been offered, such as enhancing the saliency and strength of the target (e.g., Doshier & Lu, 2000; Wolfe, 2001), inhibiting distracting information by noise reduction (e.g., Doshier & Lu, 2000; Duncan & Humphreys, 1989), and by constraining the observer's attentional set by establishing expectancy and intent (e.g., Davis & Graham, 1981; Folk, Remington, & Johnston, 1992).

One way of reducing this uncertainty is to prime the system for specific visual features (e.g., Huang & Pashler, 2005). Priming is a type of pre-cueing in which the presentation of one stimulus (the prime) affects judgments about subsequently viewed stimuli, such as judgments about identity. When a prime is closely related to or identical with a target, it can lead to benefits in performance, such as increased accuracy or quicker

response time (e.g., Perea & Rosa, 2000; Posner, 1980; Posner & Snyder, 1975). If the prime is very different from or conflicts with the target, it can lead to costs in performance, such as decreased accuracy and slower response time (e.g., Posner, 1980; Posner & Snyder, 1975; Tipper, 2001). Priming can even override expectancy effects early in processing (e.g., Hailston & Davis, 2006; Posner, 1980). These changes presumably occur without any intention and even in the absence of memory for the prime (Meyer & Schvaneveldt, 1971), suggesting that these changes are both involuntary and unconscious.

There is ample evidence that visually priming one feature dimension, such as color, can affect search performance (e.g., Grice & Gwynne, 1985; Hailston & Davis, 2006; Huang & Pashler, 2005; Laarni & Haakkinen, 1994; Maljkovic & Nakayama, 1996; Posner, 1980; Theeuwes, 1995; Wolfe, 1994). But, little data exist examining if any additional effects are derived from simultaneously priming multiple features. One exception to this is a study by Kristjansson (2006).

Kristjansson's study investigated the effects of multiple-feature priming using repetition priming, where targets on one trial serve as the prime for targets on subsequent trials. So, repetition priming relies on observers both apprehending and remembering stimuli from trial to trial. Kristjansson had participants search for Gaussian blobs defined by three different features: color, spatial frequency, and orientation. He found task-relevant features that defined either the target or response always resulted in priming effects (e.g., reduced response time, RT). Furthermore, he demonstrated that color always produced priming effects even when it provided *no* information about either the target or the response (Kristjansson, 2006). More importantly, Kristjansson found that

priming multiple features produced no additional benefits on overall RT. One possible explanation for this result is the choice of features used in his study. As discussed previously, in feature processing those neurons that process spatial frequency are difficult to dissociate from neurons which process other feature dimensions (e.g., color or orientation). Perhaps any effects of priming multiple features were lost due to the overlap in processing resources for these feature dimensions. The current experiments use features that are perceptually distinct from one another in an attempt to control for this potential confound.

Theoretically, priming should increase the level of bottom-up activation associated with the primed features. In the case of valid primes, this should guide attention to the correct item in the display, and reduce decision noise that results from presenting non-target distractors in the display. Thus, valid priming of relevant feature dimensions should improve performance on triple-conjunction and whole-object search and should result in additional performance benefits as the number of primed features is increased. Conversely, one might expect an invalid prime, priming features which are *not* present in the subsequent target, should harm performance and that performance should become worse as the number of invalidly primed features is increased. The second and third experiments in this dissertation address the issue of priming multiple feature dimensions, and in Experiment 3, the entire object itself.

These last two experiments employed an explicit priming paradigm to examine the effects of priming color, orientation, motion or, in Experiment 3, also priming the entire object. That is, in these experiments each search display was preceded by a prime stimulus on a trial-by-trial basis. This allowed the effects of simultaneous priming on

performance to be observed without relying on the participant's ability to implicitly perceive and process targets across trials, as was done in repetition priming studies.

In addition to offering insight into the nature and limits of priming effects in visual search, answering these questions also offers us practical value as well. As discussed previously, we can observe situations where sensitivity to one feature is diminished while sensitivity to others is left intact. Therefore, if we can observe additional benefits from priming multiple features, we should be able to improve performance for persons who suffer from some perceptual deficiencies without harming performance of those who do not.

Overview and Purposes of Experiments

To address the issues raised in this Introduction, I conducted a series of three experiments. The first experiment compared the theoretical predictions about performance in both single-feature search and triple-conjunction search in which the target shared only one feature with any distractor. The second experiment examined the effects of priming multiple features on a triple-conjunction task in which targets and distractors were defined exclusively by the three features of interest – color, orientation, and motion. The third experiment examined not only multiple feature priming but also object priming in a more complex object search task. In both Experiments 2 and 3 the target could share either one or two features with any distractor.

The specific questions addressed in these experiments are:

- Which of the three models best predicts performance in triple conjunction searches as compared to simple feature search?

- What happens when we prime multiple features on the same trial? Do we see an increased effect if we prime two features as compared to only priming one?
What about priming three features simultaneously? Does simply priming the object itself offer any real benefit above and beyond feature priming?
- Are some features more effective valid primes than others? And, by the same token, do some features have a larger negative effect on performance when they are invalidly primed?
- Are there any ceiling effects for the number of validly-primed features? Any floor effects for the number of invalidly-primed features?
- Are the observed effects the same for both identification and localization tasks? Or does the type of response limit the effects of priming?
- Are these observed effects stimulus dependent? That is, do we observe similar effects in triple-conjunction searches where the features explicitly define the stimuli as we do in whole-object search tasks?
- Finally, can the models be conceptually expanded to predict priming effects when distractors share more than one feature with a target stimulus? If so, how do their respective predictions compare to the observed data in Experiments 2 and 3?

CHAPTER II

EXPERIMENT 1: COMPARING THEORETICAL PREDICTIONS

In this experiment the predictions made by the three models of visual search were compared against observed performance. The three models were Lavie's Perceptual Load Theory (Lavie, 1995), Wolfe's Guided Search (Wolfe, 1994), and Eckstein's Multi-Dimensional Signal Detection Model (Eckstein et al., 2000). All three models predict relatively flat search slopes (i.e., little or no set-size effects) for simple feature searches, such as searching for a red target among homogeneous green distractors. However, the three models make markedly different qualitative predictions about performance in a triple-conjunction search in which the target differs from each distractor along two feature dimensions, but shares one feature.

Lavie's PLT (1995) predicts large set-size effects in the triple-conjunction search due to the increased perceptual load associated with the added feature dimensions, as described in the Introduction. Wolfe's GS model predicts relatively equal performance in both search conditions (Wolfe, Cave, & Franzel, 1989), and Eckstein's multi-dimensional SDT model (2000) predicts better performance in the triple-conjunction search than in the simple feature search because in the triple-conjunction search information for targets is combined across three feature dimensions, and each distractor differs from the target along two of those dimensions. Thus, the target is much more likely to elicit a larger response than any single distractor.

Method

Participants

Twelve undergraduate students (six males and six females) from the Georgia Institute of Technology participated in this experiment. They had a mean age of 19.75 yrs ($SD = 1.55$ yrs). All participants had normal or corrected to normal visual acuity for near distances. None of the participants displayed any astigmatism or color vision deficiencies.

Apparatus and Materials

Two Dell Optiplex computers with Sony Trinitron 19" color monitors and standard keyboards were used in this experiment. Computer programs written in Psychology Software Tools' E-prime version 1.1 (Psychology Software Tools, 1999) were used to control stimulus presentations and to record participants' responses.

Screening for both visual acuity and astigmatism were conducted using E-chart version 2.3.1 (Buehnerkemper, 2003). This program allows each participant to be tested at the same viewing distance as the experimental testing (28.5 inches). Color vision was screened using Ishihara color plates with a standard C illuminant (Ishihara, 1997).

Stimuli

The visual stimuli were defined by three feature dimensions. In the color feature search, the target was a red, vertical bar and distractors were green, vertical bars. In the orientation feature search, the target was a red, vertical bar and distractors were red, horizontal bars. In the motion feature search the target was a red, vertical bar that moved toward the right and distractors were red, vertical bars that moved toward the left.

In the triple-conjunction search, the target was a red, vertical bar that moved toward the right. Distractors were any combination of red or green, vertical or horizontal bars that moved either to the left or the right. The only limitation was that each distractor shared *only one* of the target's features – this constraint was mandated by the assumptions of the specific models. For example, a distractor may be red, but horizontally oriented and moving to the left.

Each trial contained only one target. All stimuli (targets and distractors) were arranged so that they appeared at equidistant points from a centralized fixation cross in order to rule out perceptual discrepancies (e.g., retinal eccentricity effects) as the cause of any observed set-size effects (e.g., Geisler & Chou, 1995; Palmer, 1995). Furthermore, all stimuli were constructed so that at a viewing distance of 28.5 inches each subtended a visual angle of 2.5°.

Procedure

Prior to experimental testing, each participant was screened to ensure normal or corrected-to-normal visual acuity for near distances, no indication of astigmatism, and no color vision deficiencies. After all pre-experimental screening was completed, participants began the experiment. Each participant completed four different search conditions. Three of these were simple feature searches (color, orientation, or motion) and the fourth was a triple-conjunction search. The order of the experimental conditions was counterbalanced across participants. Each experimental condition consisted of three blocks of trials organized by set size (2, 4, or 8 stimuli) and the order of these blocks was randomized within each condition. Each block consisted of 200 trials. The total number of trials for each participant was 2,400.

At the beginning of each trial participants were instructed to focus on a fixation cross presented in the center of the screen. When focused on the fixation cross, they initiated the trial by pressing the spacebar on their keyboard. Immediately after pressing the space bar, a search display was presented and remained on the screen for 100 ms. After the display disappeared, participants had to report in which location the target stimulus had appeared (either the top or bottom half of the display) by pressing the corresponding key on their keypads.

Accuracy rates were recorded in each of the four experimental conditions. The total time required to participate in this experiment was 2 hours. Appropriate rest breaks were given during the experiment, between the experimental conditions.

Results and Discussion

In general, color was the most salient feature of the three features examined in this experiment. Feature-search performance was better in the color search than in either the orientation or motion search, regardless of set size. There were no performance differences between the motion and orientation searches. The triple-conjunction search yielded better performance than either the orientation or the motion feature search, but it did not differ from the color feature search. The analyses and implications of these results obtained are described below.

Empirical Results

A repeated measures ANOVA revealed significant effects for both set size ($F(2,22) = 18.746; p < 0.001$) and search condition ($F(3,33) = 7.095; p = 0.001$). There was no significant set size by search condition interaction. Figure 2 illustrates the results for all four search conditions.

Accuracy as a Function of Set-size

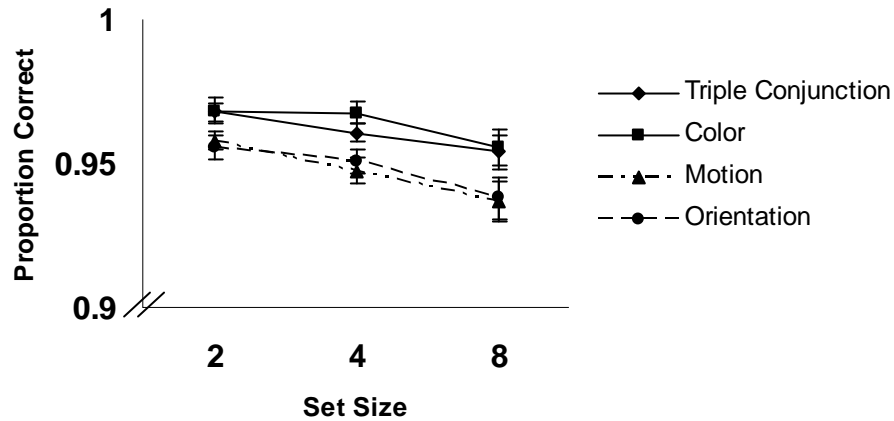


Figure 2. Group data for the four search conditions. Error bars represent \pm one SEM.

Follow-up analyses compared each search condition to every other one. Each of these was a 2 by 3 repeated measures ANOVA. The two within-subjects factors were search condition (e.g., color, orientation, motion, or triple-conjunction) and set-size (2, 4, and 8). There were no significant search types by set size interactions in any of the six comparisons. Table 1 lists the significant results of these ANOVAs.

Table 1

| <i>Comparisons of Search Conditions</i> | | | | |
|---|-----------------|----------------|-----------------|----------------|
| Search Types | Search | | Set-size | |
| | <i>F</i> (1,11) | <i>p</i> value | <i>F</i> (2,22) | <i>p</i> value |
| Color-Orientation | 19.963 | 0.001 | 19.789 | < 0.001 |
| Color-Motion | 6.498 | 0.027 | 25.37 | < 0.001 |
| Color-TC | 2.462 | 0.145 | 13.55 | < 0.001 |
| Orientation-Motion | 0.01 | 0.924 | 20.641 | < 0.001 |
| Orientation-TC | 17.405 | 0.002 | 9.963 | 0.001 |
| Motion-TC | 5.802 | 0.035 | 8.363 | 0.002 |

Comparison to Theoretical Predictions

With regard to the theoretical predictions made by the three visual search models, we can safely rule out PLT as the best predictor. Recall that PLT predicts worse performance for the triple-conjunction search than for any of the three single-feature searches. In the data presented here, the triple conjunction search was as good as or better than each of the three single-feature searches. Moreover, the set-size effect for TC did not differ from that for any single-feature search, as there were no significant interactions between search condition and set size.

We cannot, however, make a clear-cut distinction between GS and MDSM with regard to which best predicts performance. The GS model predicts equivalent performance for single-feature and triple-conjunction searches. This was the case when comparing the color search to the triple conjunction search so that GS was the best predictor of performance. Moreover, there is no significant interaction between search condition and set-size effect for any comparison with triple-conjunction, just as the GS model predicts.

When we compare both the orientation and motion searches to the triple conjunction search, however, we see significantly better performance for the triple conjunction task. The results from these comparisons lend more support to MDSM than to GS, although the set-size effect was not noticeably smaller for triple conjunction search, as MDSM suggests. Thus, it is difficult to distinguish between the two models based on the data in this experiment.

Perhaps we cannot distinguish between GS and MDSM because the chosen feature dimensions were too salient, especially with regard to color. In fact, comparing the single-feature searches to one another, we see there is no difference in accuracy between the motion and orientation searches, but accuracy in the color search is significantly better than for either motion or orientation. Perhaps the difference between red and green is so perceptually discriminable that it offers all the necessary information to successfully carry out the triple-conjunction task.

More rigorous testing is required prior to making any definitive claims as to which model best predicts performance. A better way to test these models may be to use stimuli that are not quite so discriminable. Reducing the target-distractor discriminability of each feature to introduce some confusability, and then equating this discriminability across the three different feature dimensions, would allow one to more rigorously test these models. For example, instead of red and green, the colors may be red and orange, with hues chosen so that they are somewhat confusable and also match the target-distractor discriminability of the other two features (e.g., vertical and slightly tilted bars). Such studies are planned for future research.

CHAPTER III

EXPERIMENT 2: SIMULTANEOUS FEATURE PRIMING IN TRIPLE- CONJUNCTION VISUAL SEARCH TASKS

In the second experiment I examined the effects of simultaneously priming more than one feature. Specifically, I investigated whether priming has an increased effect if more than one feature is simultaneously primed. I also examined how invalid primes affect performance as compared to valid primes. Does increasing the number of invalidly primed features hurt performance more whereas increasing the number of validly primed features helps performance more? In addition, I examined whether some features are more effective primes than others. If color is the most salient feature (as Experiment 1 suggests) then it may be the most effective prime as well. Finally, I investigated whether priming effects were the same for both identification and localization, or if they differed. In other words, does the type of response limit the effects of priming? To address these issues I conducted a visual search experiment using explicit, trial-by-trial priming, and examined target identification and target localization as a between-subjects variable. The triple-conjunction searches of Experiment 2 differ from those of Experiment 1 in that a distractor may share either one or two feature dimensions with the target, as described below.

METHOD

Participants

Twenty-four undergraduate students (eleven males and fourteen females) from the Georgia Institute of Technology participated in this experiment. They had a mean age of

19.58 yrs ($SD = 1.136$ yrs). All participants were screened to ensure they had no color vision abnormalities (e.g., red-green color deficiency), no astigmatism, and that they had 20/40 or better visual acuities for the experimental viewing distance wearing any necessary corrective eyewear.

Apparatus and Materials

The apparatus and materials used in this experiment were the same as those described in Experiment 1.

Design

This experiment used a mixed measures design. Two within-subjects factors and one between-subjects factor were examined. The two within-subjects factors were set size and primed feature. The between-subjects factor was type of response (target identification vs. localization).

Stimuli

The stimuli used in this experiment were defined by three perceptually distinct features: color (red or green), orientation (vertical or horizontal), and motion (left or right). Two target stimuli (Targets A and B) were used. Target A was a red, vertical bar that moved toward the right along a horizontal plane, whereas Target B was a green, horizontal bar that moved toward the left. The distractors were designed so that each shared one or two feature dimensions with the target stimuli. For example, a distractor may have the same color as Target A and the same orientation and direction of motion as Target B. This is different from Experiment 1, where each distractor shared only one feature dimension with the target.

Prime Stimuli

Half of the primes in this experiment were valid primes (i.e., shared at least one feature with the subsequent target stimulus), and the others were invalid primes (i.e., shared features with the other target, not with the target shown on that trial). Using primes that were valid on only 50% of the trials allowed me to examine the effects of priming independently of any potential expectancy effects (e.g., Hailston & Davis, 2006). Table 2 lists the 16 different priming conditions used in this experiment.

Table 2

Primes used in Experiment 2

| Prime | Prime Stimulus |
|-------------------------------|---|
| No Prime | None |
| Neutral Prime | Black, stationary circle |
| Color prime | Stationary, red or green circle |
| Orientation Prime | Stationary, black, vertical or horizontal bar |
| Motion Prime | Black circle that moved toward either the right or left |
| Color + Orientation | Either a red, vertical bar or a green, horizontal bar |
| Color + Motion | Either a red circle moving toward the right, or a green circle moving toward the left |
| Orientation + Motion | Either a black, vertical bar moving toward the right, or a black horizontal, bar moving toward the left |
| Color + Motion + Orientation* | A red, vertical bar moving toward the right, or a green, horizontal bar moving toward the left |

*The triple-feature prime is identical with one of the targets.

On some trials no prime was displayed. These trials offered a true baseline measure of accuracy for the search task itself. The neutral prime used in this experiment was a stationary, black circle that shared no features with either target, and offered no perceptual information about the upcoming target stimulus. Comparing the neutral prime

to the no prime condition lets one determine if simply having a prime stimulus had any effect on performance (i.e., if any prime matters more than no prime at all).

The single-feature primes each shared one feature (color, orientation, or motion) with one of the two target stimuli. These were used to determine (a) if a feature prime has more effect on performance, either positively for a valid prime or negatively for an invalid prime, than a neutral prime as well as (b) which of the three features may have a greater effect on performance, perhaps due to salience.

The two-feature primes each shared two features with only one of the two target stimuli. These paired feature primes were used to determine (a) whether priming more than one feature leads to additional performance benefits for valid primes or costs for invalid primes, and (b) which pairings may have greater impact on performance, perhaps due to salience of the paired features.

The three-feature primes were identical to one of the two target stimuli. By comparing the three-feature prime to the two-feature prime I could determine (a) if the three-feature prime had an even greater impact on performance, (b) if there were any ceiling effects for valid feature priming or (c) if there were any floor effects for invalid feature priming.

Each trial contained only one target in the search display. Like the previous experiment, stimuli were arranged so that they appeared at equidistant points from a centralized fixation cross, and so that at a viewing distance of 28.5 inches they each subtended a visual angle of 2.5°.

Procedure

Half of the participants had to identify which of two targets was presented, and the other half had to localize the target on either the top or bottom half of the display. Participants completed six blocks of trials grouped by set size (2, 4 or 8 stimuli). The order of blocks was randomized within an experimental condition. Every block consisted of 400 trials for a total of 2,400 trials. In each block there were 25 trials for the no-prime condition and for each of the primes shown in Table 2. Thus, one could observe and compare each prime's effectiveness for localizing or identifying target stimuli.

On every trial, except the no-prime trials, a prime appeared in the middle of the screen and remained for 100 ms. Afterwards, it was replaced by the search display, which remained on the screen for 150 ms. When the search display disappeared, one group of participants had to identify which of two target stimuli had been presented in the display, whereas the other group had to locate whether the target had been presented on the top or bottom of the display¹. Given there were only two possible responses in a given trial (viz., 2 AFC trials), chance performance was constant at 50% across all experimental trials, regardless of set size (2, 4, or 8) or of type of response (identification or localization).

Participants were instructed to take as much time as necessary to ensure maximum accuracy, and response accuracy was recorded.

¹ By localizing targets to either the top or bottom half of the display, one can rule out any spatial Stroop or Simon effects (Simon, 1969) that may have resulted from the leftward and rightward motion of the individual stimuli.

Results and Discussion

As a preview of the results and discussion, there were several noteworthy findings. First, validly primed features improved search performance, and priming more features resulted in larger effects. Moreover, valid priming of any feature had a greater impact on performance than did either a neutral prime or no prime at all. Second, invalid primes had no effects on accuracy – performance was the same as in the no-prime and neutral prime conditions. Third, color was the most salient feature, similar to results reported in Experiment 1. Finally, the patterns of results were similar for both target identification and target localization. So, in the analyses described below, the data were collapsed across both the target identification and localization. Because there were no effects of invalid primes the analyses on these are not included in this section, but can be found in Appendix A.

Neutral Prime vs. No Prime Condition

To address whether simply having any prime (even if it is irrelevant) is better than having no prime at all, the data for the neutral prime and no prime conditions were compared. A 2 (neutral prime vs. no prime) by 3 (set size) repeated-measures ANOVA revealed a significant effect of set size ($F(2,46) = 281.752; p < 0.001$), but no effect of priming condition and no significant interaction (see Figure 3). Thus, we can dismiss the argument that simply having *any* prime stimulus results in observable benefits or costs to performance, as compared to having no prime at all.

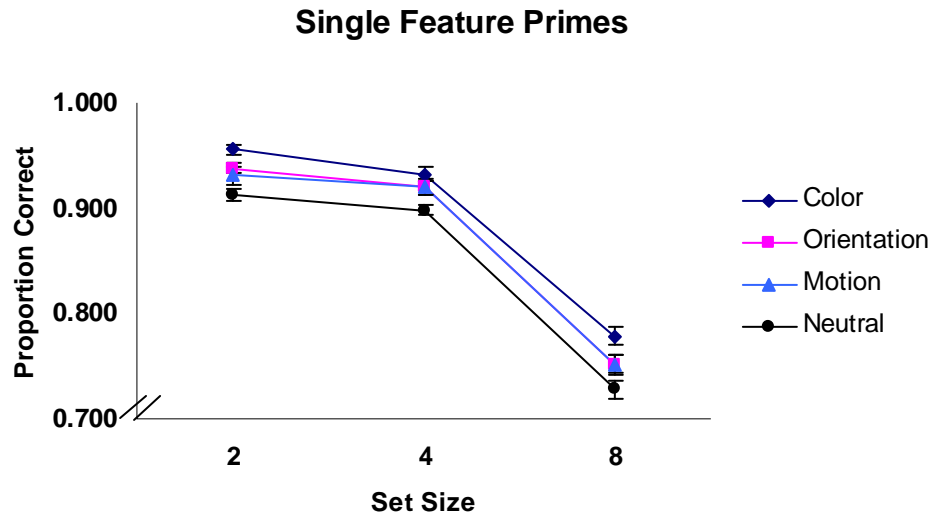


Figure 3. Accuracy performance for single feature primes plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

One Feature Primes vs. Neutral Prime Condition

The next issue was whether, as a whole, the single feature primes resulted in any real, observable effects on performance as compared to the neutral prime. To address this, a 2 (feature vs. neutral prime) by 3 (set size) repeated measures ANOVA was conducted, which revealed a significant effect for both set size ($F(2, 46) = 323.361$; $p < 0.001$) and for priming condition ($F(1,23) = 11.359$; $p = 0.003$), but no significant interaction. Thus, in this experiment valid feature primes did result in benefits to search performance as compared to neutral prime conditions (see Figure 3). Consequently, we can examine the effects of priming multiple feature dimensions on search performance. Table 3 lists the group means and standard deviations for each of the three features examined and the neutral prime condition.

Table 3

| <i>Means and Standard Deviations for Single Feature and Neutral Primes</i> | | |
|--|-------|--------------------|
| Condition | Mean | Standard Deviation |
| SS2 Neutral | 0.914 | 0.027 |
| SS2 Color | 0.956 | 0.022 |
| SS2 Orientation | 0.938 | 0.024 |
| SS2 Motion | 0.931 | 0.044 |
| SS4 Neutral | 0.918 | 0.049 |
| SS4 Color | 0.933 | 0.029 |
| SS4 Orientation | 0.920 | 0.031 |
| SS4 Motion | 0.921 | 0.036 |
| SS8 Neutral | 0.724 | 0.064 |
| SS8 Color | 0.779 | 0.021 |
| SS8 Orientation | 0.752 | 0.048 |
| SS8 Motion | 0.752 | 0.041 |

Effects of Priming Multiple Features

One main purpose of this experiment was to examine whether simultaneously priming multiple feature dimensions yield larger effects on search performance as the number of primed features increases. To determine this, a 3 by 3 repeated-measures ANOVA was conducted. The two factors were priming condition (1 vs. 2 vs. 3 features) and set size (2, 4, and 8). This ANOVA revealed main effects for both set size ($F(2,46) = 550.515$; $p < 0.001$) and the number of features primed ($F(2,46) = 30.996$; $p < 0.001$). When more features were simultaneously primed, there was a greater effect on performance. There were no significant interactions.

Difference contrasts revealed that validly priming two ($M = 0.885$; $SEM = 0.003$) features resulted in better performance than priming only one ($M = 0.875$; $SEM = 0.003$) ($F(1,23) = 9.022$; $p = 0.006$), and priming all three features ($M = 0.906$; $SEM = 0.004$)

yielded even better performance than priming two features ($F(1,23) = 31.736$; $p < 0.001$), as shown in Figure 4.

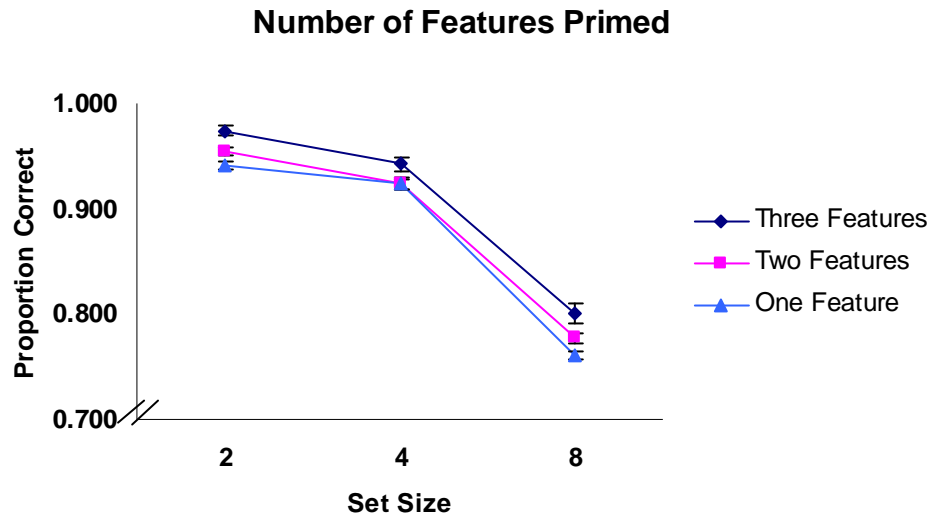


Figure 4 – Accuracy levels for varying priming conditions plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

Salience of Feature Dimensions (Color vs. Orientation vs. Motion)

Comparing Single Feature Primes

To examine which of the three features produced the largest effects on performance, a 3 by 3 repeated-measures ANOVA was conducted. The two within-subjects factors were set size (2, 4, and 8), and feature (color vs. orientation vs. motion). Significant effects for both set size ($F(1,46) = 622.450$; $p < 0.001$) and primed feature ($F(2,46) = 10.853$; $p < 0.001$) were revealed – there were no significant interactions. See Figure 4.

Follow-up, planned comparisons were conducted to determine whether (a) each valid feature yielded performance benefits above and beyond a neutral prime, and (b)

which of the three features was the best prime stimulus. Table 4 lists the results of these individual comparisons.

Table 4

| <i>Single Feature Primes vs. Neutral or Other Features</i> | | |
|--|-----------------|----------------|
| Comparison | <i>F</i> (1,23) | <i>p</i> value |
| Color - Neutral | 24.071 | < 0.001 |
| Orientation - Neutral | 5.253 | 0.031 |
| Motion - Neutral | 4.505 | 0.045 |
| Color - Orientation | 18.462 | < 0.001 |
| Color - Motion | 15.554 | 0.001 |
| Orientation - Motion | 0.138 | 0.714 |

Each valid feature resulted in increased benefits to performance as compared to the neutral prime condition. Although there was no statistical difference between the effects of priming orientation and motion, color primes resulted in larger performance benefits than either orientation or motion primes. Thus, in this experiment color was the most salient feature.

Comparing Paired Feature Primes

If color was indeed the most salient feature, then one would expect that paired feature primes involving color would result in larger effects on performance than those that do not. This is indeed what was found. A 3 (prime pairings) by 3 (set size) repeated-measures ANOVA revealed significant effects of prime pairs ($F(2,46) = 7.253$; $p = 0.002$) and set size ($F(2,46) = 471.382$; $p < 0.001$).

Planned comparisons confirmed again that color produced the largest effects on performance. Regardless of which feature it was paired with, valid-prime pairs involving

color resulted in better performance than when orientation and motion were paired together. Furthermore, there was no difference between the color-orientation and the color-motion pairs (see Figure 5). Table 5 lists the results of these planned comparisons.

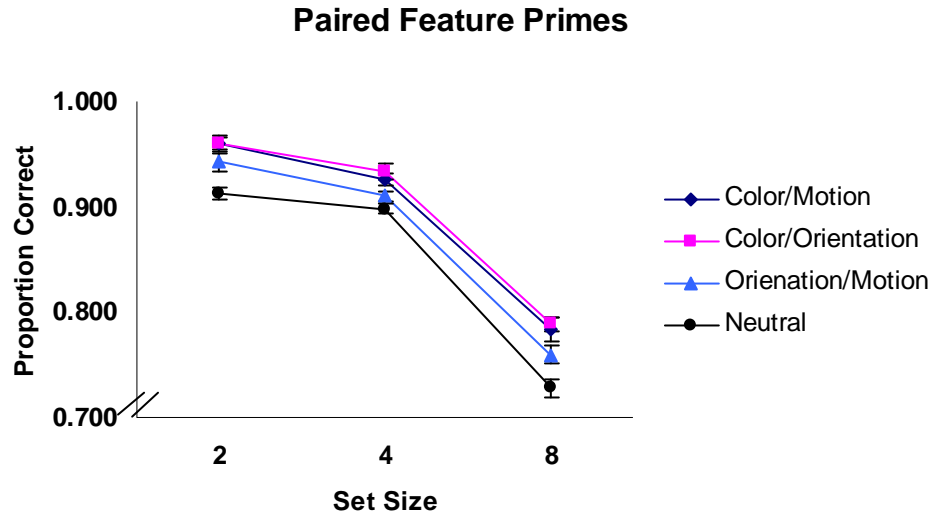


Figure 5 – Accuracy performance for paired feature primes plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

Table 5

| Comparison | <i>F</i> (1,23) | <i>p</i> value |
|--------------------------------------|-----------------|----------------|
| Color-Motion/Color-Orientation | 0.341 | 0.565 |
| Color-Motion/Orientation-Motion | 15.577 | 0.001 |
| Color-Orientation/Orientation-Motion | 7.475 | 0.012 |

Further Analysis of Individual Features

The final analyses involved examining the individual features and what benefits each incurred when coupled with others. To do this, I conducted a 4 by 3 mixed-measures ANOVA for each of the individual feature dimensions. The two within-subjects factors were primed feature dimensions (e.g., color, color + orientation, color + motion, and

color + orientation + motion) and set size (2, 4, and 8). The between-subjects factor was type of response (identification vs. localization). There were no significant effects of response type (identification vs. localization), nor any significant interactions involving response type. Thus, the following analyses collapsed data across target identification and localization responses. Figure 6 shows the data for each specific feature and its pairings. Again, only data for validly-primed trials are shown below.

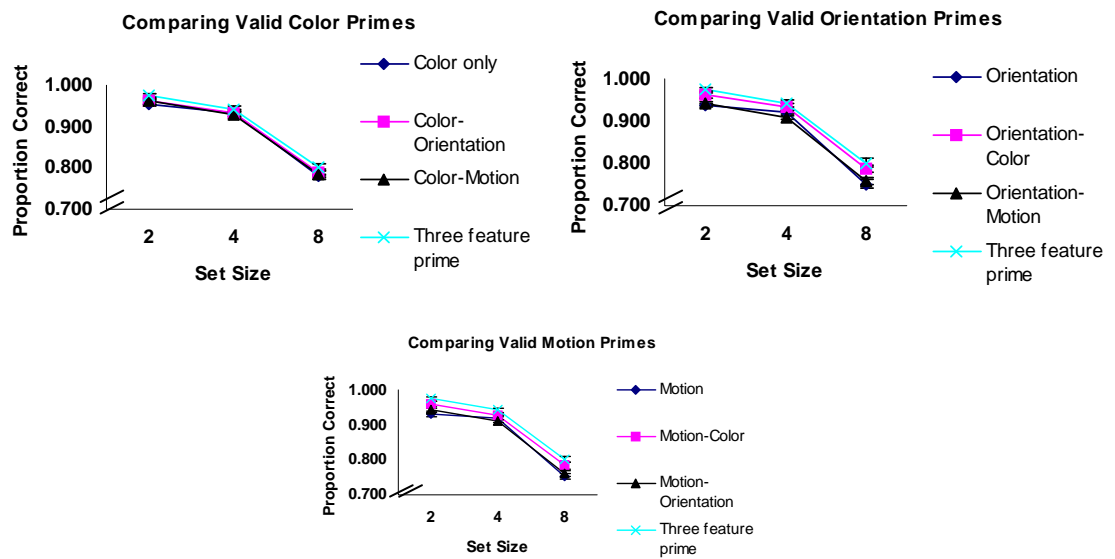


Figure 6. – Comparing primes involving each feature dimension. Error bars represent ± 1 SEM.

Color Primes

The mixed-measures ANOVA conducted on the four color prime conditions revealed a significant effect of set size ($F(2,46) = 523.974$; $p < 0.001$) but no other main effects or interactions.

Orientation Primes

The analysis of the orientation primes revealed a significant main effect for both set size ($F(2,46) = 493.443; p < 0.001$) and number of validly-primed dimensions ($F(3,69) = 21.217; p < 0.001$), but no significant interactions. In this condition, the color+orientation and the color+orientation+motion primes yielded significantly better performance than either the orientation or the orientation+motion primes. Furthermore, the orientation+motion prime resulted in larger effects on performance than the orientation prime.

Motion Primes

Significant main effects of both set size ($F(2,46) = 358.499; p < 0.001$) and number of validly-primed dimensions ($F(3,69) = 16.402; p < 0.001$) were revealed. Again, there were no significant interactions. Primes involving the color feature resulted in better performance than both the orientation+motion and motion-only primes.

These results confirm that color was the most salient feature in this experiment, as found in the previous experiment. When performance was compared between the color prime and the combined features primes involving color (i.e., color-orientation, color-motion, color-motion-orientation) no significant effects on performance were discovered. When the same comparisons were conducted on either the orientation or the motion prime, we again see pairings involving color consistently yielding better performance than did motion or orientation alone or when orientation and motion are combined. Pairing motion or orientation with color yielded performance similar to that of the triple-feature prime.

CHAPTER IV

EXPERIMENT 3: SIMULTANEOUS FEATURE PRIMING IN WHOLE-OBJECT VISUAL SEARCH TASKS

As discussed in Chapter I, although early in the human visual system items in the environment are processed at the level of feature components, we do not perceive our world as a mass of individual features, but rather as whole objects. Because of this, I examined how the results of priming in triple-conjunction search would compare to priming multiple features in whole-object search.

In this final experiment, I used the same basic methods from the second experiment. That is, I conducted a visual search experiment using explicit, trial-by-trial priming, and examined target identification and target localization as a between-subjects variable.

METHOD

Participants

Twenty-four undergraduate students (eleven males and fourteen females) from the Georgia Institute of Technology participated in this experiment. They had a mean age of 19.58 yrs ($SD = 1.136$ yrs). All participants were screened to ensure they had no color vision abnormalities (e.g., red-green color deficiency), no astigmatism, and that they had 20/40 or better visual acuities for the experimental testing distance after any necessary corrective eyewear.

Apparatus and Materials

The apparatus and materials used in this experiment were the same as those described in Experiment 1.

Stimuli

Each trial contained only one target in the search display. As in the previous experiments, stimuli were arranged so that they appeared at equidistant points from a centralized fixation cross, and so that at a viewing distance of 28.5 inches they each subtended a visual angle of 2.5°.

Target and Distractor Stimuli

The target and distractor stimuli used in this experiment are shown in Figure 7. They all consisted of three geometric components (e.g., triangle, circle, and rectangle) arranged vertically in the same overall structural arrangement (e.g., Newell, Brown, and Findlay, 2004), although their component parts differed slightly in some metric (e.g., an ellipse instead of a rectangle). In addition to the geometric shapes that make up the stimuli, the color, direction of motion, and orientation of both targets and distractors was also manipulated.

The two target stimuli (A and B) differed slightly in their three geometric components, but had the same overall structural arrangement. Target A was red, vertically oriented, and moved toward the right. Target B was green, horizontally oriented, and moved toward the left. The distractor stimuli (1 and 2) each contained at least one same feature dimension value, and one geometric component as each target stimulus. For example, Distractor 1 shared the vertical feature, and circle component with Target A, and the green color feature, and trapezoid component with Target B (see Figure 7). The distractors also shared the same overall structural arrangement as the target stimuli. Thus, the target stimuli were more similar to either of the two distractors than they were to each other, as shown in Figure 7.

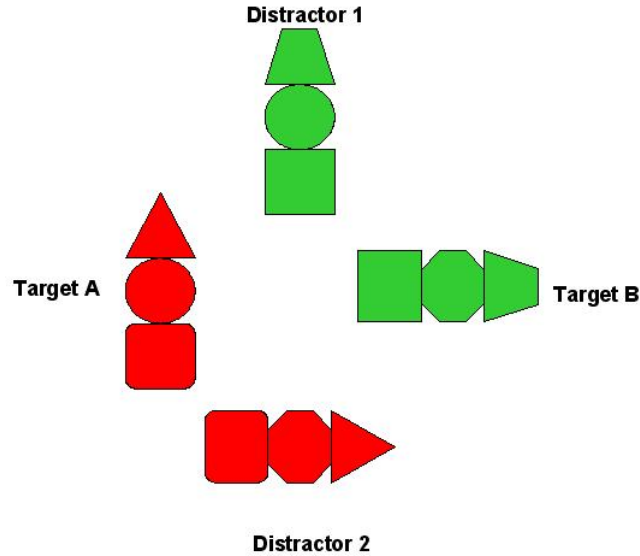


Figure 7. Stimuli used in Experiment 3. Stimuli are arranged to spatially represent similarity between targets and distractors, not as they appeared within a search trial. Each distractor stimulus contains at least one geometric element of each of the two target stimuli, thus each target stimulus is more similar to either distractor than to the other target stimulus.

Prime Stimuli

The prime stimuli used in this experiment were the same as those used in Experiment 2 with one exception. In addition to the primes used in Experiment 2, trials were included in which the object themselves were used as primes. As with all other priming conditions, half of the object primes were valid and the other half were invalid.

Procedure

The procedures in this experiment were the same as those used in Experiment 2.

Results and Discussion

As a brief overview of the results, several results in this experiment were similar to those in Experiment 2. As in Experiment 2, validly-primed multiple features did have an effect – priming more features resulted in larger effects. However, there were no

observed benefits of priming the whole object above and beyond priming the three feature dimensions of color, orientation, and motion.

Again, any single-feature valid prime had a greater impact on performance than either a neutral prime or no prime at all. And invalid primes had no effect on accuracy – performance was the same as with either the neutral or no prime condition. Once again, color was the most salient feature, similar to the results reported in the first two experiments. As in Experiment 2, the patterns of results were similar for both target identification and target localization. As a result, the data were collapsed across both the target identification and localization groups in the analyses described below. Because there were no effects of invalid primes, these analyses are not included in this chapter, but can be found in Appendix B.

Neutral Prime vs. No Prime Condition

As in the previous experiment I first examined whether there were any difference between the neutral prime and no-prime conditions. A 2 by 3 repeated-measures ANOVA revealed only a significant effect of set size ($F(2,46) = 52.165; p < 0.001$). So, in this experiment we can again dismiss the argument that simply having a neutral prime stimulus results in observable benefits or costs to performance, as compared to having no prime at all.

One Feature Primes vs. Neutral Prime Condition

A 2 by 3 repeated-measures ANOVA revealed significant effects for both set size ($F(2, 46) = 63.305; p < 0.001$) and for priming condition ($F(1,23) = 48.221; p < 0.001$), but no significant interactions. As in the previous experiment, valid-feature primes did

result in benefits to search performance, as compared to the neutral prime condition (see Figure 8).

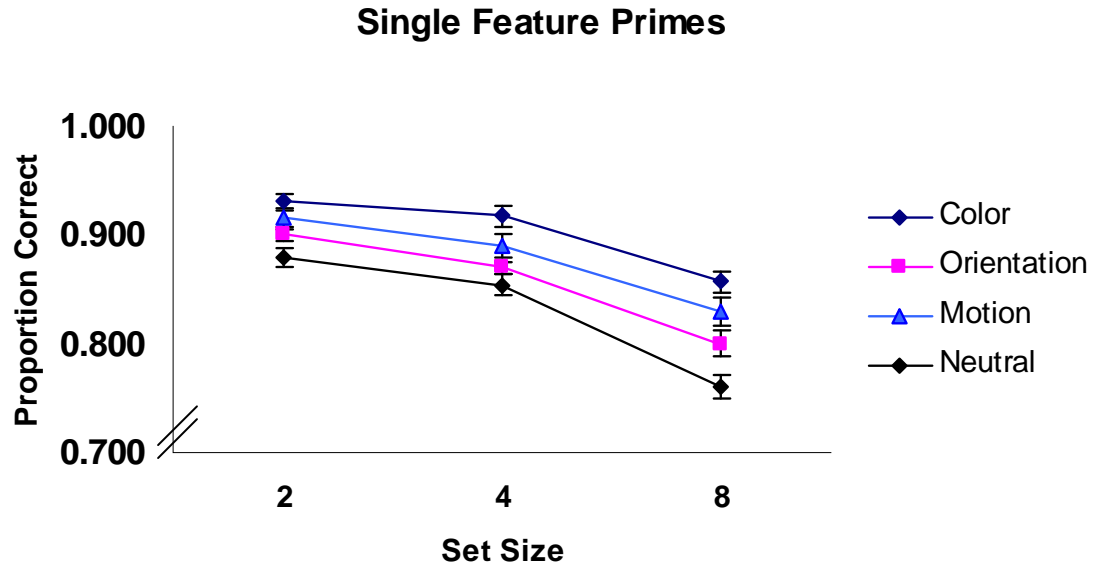


Figure 8 - Accuracy performance for single feature primes plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

Effects of Priming Multiple Features

One major purpose of this experiment was to examine whether performance in object visual search derived additional benefits from simultaneously priming multiple valid feature dimensions, similar to those observed for triple-conjunction visual search in Experiment 3. Another major purpose was to examine whether priming the target object with itself resulted in even increased benefits beyond those obtained with valid multiple-features primes. To evaluate this claim, a 4 by 3 repeated-measures ANOVA was conducted. The two within-subjects factors were priming condition (1 vs. 2 vs. 3 features vs. whole object primes) and set size (2, 4, and 8).

The ANOVA results showed main effects for both set size ($F(2,46) = 36.944$; $p < 0.001$) and the number of features primed ($F(2,46) = 17.724$; $p < 0.001$).

As in Experiment 2, priming two features resulted in better performance ($M = 0.894$; $SEM = 0.007$) than priming one feature ($M = 0.879$; $SEM = 0.005$). Priming three features ($M = 0.919$; $SEM = 0.010$) resulted in better performance than priming only two. However, there was no significant difference between the three-features prime and the whole-object prime ($M = 0.921$; $SEM = 0.007$). There also was no significant set size by number of features primed interaction. See Figure 9.

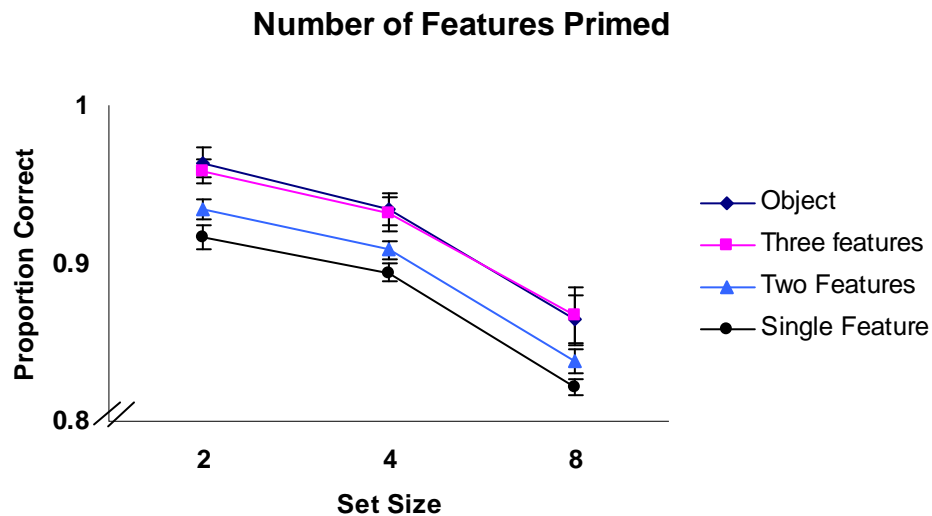


Figure 9 – Accuracy levels for varying priming conditions plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

Saliency of Feature Dimensions (Color vs. Orientation vs. Motion)

Comparing Single Feature Primes

The results of the single-feature primes are similar to those from Experiment 2. Again, a 3 by 3 repeated-measures ANOVA revealed significant main effects for both set

size ($F(2,46) = 22.494$; $p < 0.001$) and primed feature ($F(2,46) = 8.994$; $p = 0.001$), but no significant interactions. (See Figure 8).

Table 6 lists the results of the planned comparisons pitting each feature against the neutral prime or one of other two features. As in the Experiment 2, every single-feature prime resulted in better performance than the neutral condition. And, once again color resulted in the largest effects on performance.

Table 6
Comparing Neutral and Single Feature Primes

| Comparison | $F(1,23)$ | p value |
|-----------------------|-----------|-----------|
| Color - Neutral | 61.912 | < 0.001 |
| Orientation - Neutral | 19.202 | < 0.001 |
| Motion - Neutral | 15.099 | 0.001 |
| Color - Orientation | 13.749 | 0.001 |
| Color - Motion | 15.534 | 0.001 |
| Orientation - Motion | 4.505 | 0.045 |

Comparing Paired Feature Primes

As in the previous two experiments, color was the most salient feature. A 3 by 3 repeated-measures ANOVA revealed significant effects of prime pairs ($F(2,46) = 13.371$; $p < 0.001$) and of set size ($F(2,46) = 27.135$; $p < 0.001$), but no significant interaction.

Table 7 lists the results of these planned comparisons, pitting each feature pair against the others. The primes involving color (color-orientation and color-motion) resulted in larger effects on performance than the other prime pair (orientation-motion). Moreover, the prime pairs with color did not significantly differ from one another – see Figure 10.

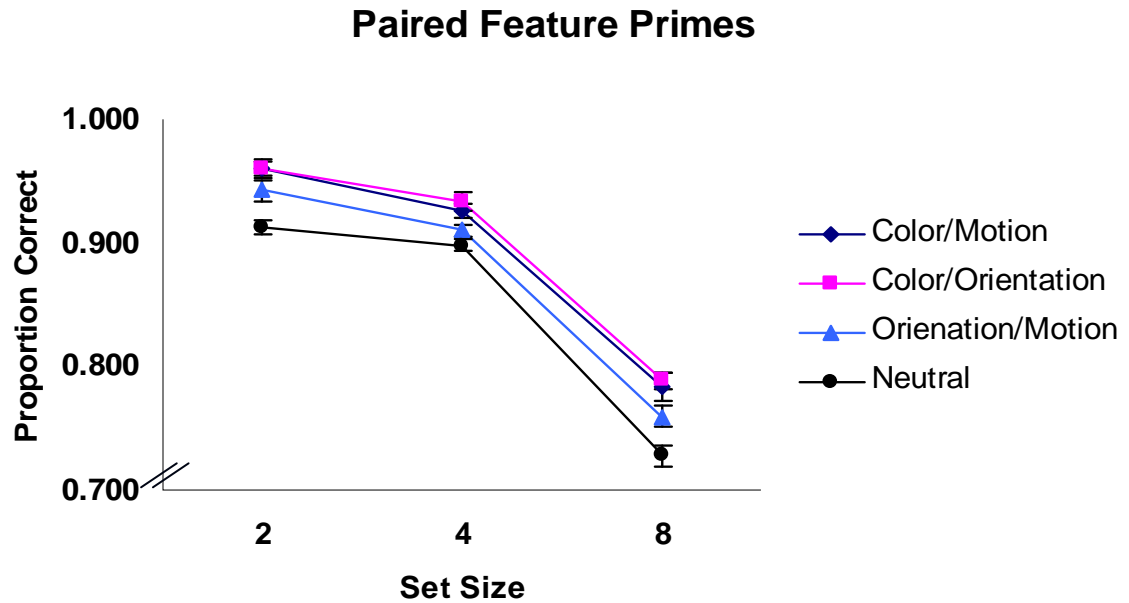


Figure 10 – Accuracy performance for paired feature primes plotted as a function of set size. Error bars represent ± 1 SEM. Bars not visible are subsumed by the respective data points.

Table 7

| <i>Comparison of Paired Feature Primes</i> | | |
|--|-----------------|----------------|
| Comparison | <i>F</i> (1,23) | <i>p</i> value |
| Color-Motion/Color-Orientation | 0.001 | 0.975 |
| Color-Motion/Orientation-Motion | 16.214 | 0.001 |
| Color-Orientation/Orientation-Motion | 17.566 | < 0.001 |

Further Analysis on Individual Features

Finally, a 5 by 3 mixed-measures ANOVA was conducted on the data for all priming conditions involving a given feature dimension (similar to those conducted in Experiment 2). The two within subjects factors were dimensions primed (e.g., color, color + orientation, color + motion, color + orientation + motion, and whole object primes) and set size (2, 4, and 8). The between-subjects factor was type of response (identification vs.

localization). Again there was no between-subjects effect of response type nor any significant interactions involving response type, so the data were collapsed across target identification and localization performance for the following analyses. Figure 11 shows the data for each specific feature and its pairings.

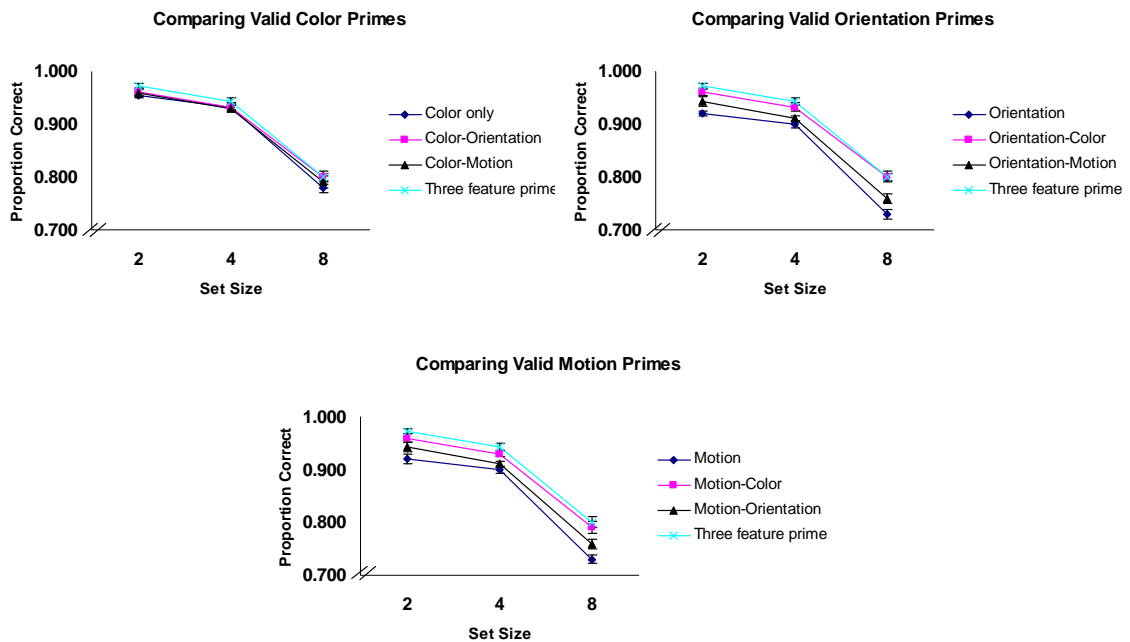


Figure 11. – Comparing primes involving each feature dimension. Error bars represent ± 1 SEM.

Color Primes

The mixed-measures ANOVA conducted on the five color prime conditions revealed only a significant effect of set size ($F(2,46) = 29.383$; $p < 0.001$).

Orientation Primes

The analysis on the orientation primes revealed a significant main effect for both set size ($F(2,46) = 40.497$; $p < 0.001$) and dimensions primed ($F(4,92) = 16.518$; $p < 0.001$). No significant interactions were revealed. In this condition the color+orientation

and the color+orientation+motion, and the whole-object primes yielded significantly better performance than either the orientation or the orientation+motion primes.

Motion Primes

Significant main effects of both set size ($F(2,46) = 36.029; p < 0.001$) and primed dimensions ($F(4,92) = 18.969; p < 0.001$) were revealed. Again, there were no significant interactions. Primes involving the color feature again resulted in better performance than the orientation+motion and motion only primes.

The results of this experiment once again indicate that color was the most salient feature. We see that in object search, much like the triple-conjunction search from Experiment 2, priming any of the three features by itself results in benefits to performance, and these benefits increase as the number of primed features increases. Interestingly, there was no further benefit of priming the entire object as compared to simultaneously priming the three feature dimensions of interest.

CHAPTER V

GENERAL DISCUSSION

The experiments reported here yield several interesting results. First, valid feature priming results in benefits to performance (i.e., increased identification and localization accuracy), and these benefits increase as the number of primed features increases (at least up to three features). Second, invalid feature primes do not result in any observable costs to either identification or localization performance, as compared to having no prime. Third, color, at least in these experiments, was the most salient of the three features primed. Finally, in their current versions, none of the three models examined in this study (PLT, GS, or MDSM) accurately predicts observed performance in all three experiments, suggesting that modifications of the models are necessary to account for perceptual priming effects. Each of these major findings and their implications are discussed in detail below.

Feature Priming

Valid primes resulted in performance benefits in the experiments reported here, consistent with previously reported results (e.g., Grice & Gwynne, 1985; Hailston & Davis, 2006; Huang & Pashler, 2005; Posner, Snyder, & Davidson, 1980). Priming any one of the three features examined in this study (color, orientation, or motion) resulted in increased accuracy compared to conditions involving either a neutral prime or no prime at all. This finding is hardly revolutionary or groundbreaking. More interesting, however, is the apparent lack of effects associated with invalid primes that we observed in the current experiments.

Priming Multiple Feature Dimensions

Another important finding is that the benefit of feature priming increases with the number of features primed. As previously mentioned, the only previous study (Kristjansson, 2006) that investigated the effects of priming multiple features reported no real effects of multiple feature priming.

The most likely reason that effects of multiple feature priming were observed in the current experiments and not in Kristjansson's work is that in the experiments reported here the features investigated are perceptually distinctive, as previously defined, and processed in at least a quasi-independent manner.

Kristjansson's decision to use spatial frequency as one of the features examined in his study presented a confound that the current experiments were able to avoid. As discussed earlier, in feature processing the same cortical cells that process color and orientation also carry spatial frequency information. Thus, it is likely that any effects of priming multiple features were lost due to the overlap in processing resources for these feature dimensions. By replacing spatial frequency with motion I was able to overcome the confound present in Kristjansson's study and obtain a clearer picture of the effects of multiple feature priming.

One might argue that the effects of multiple feature priming observed in the experiments reported here were due to the salience of the color feature. Perhaps, because color is so salient, it is not the number of features primed that mattered, but rather how color played into these calculations. For example, with single feature primes each of the three features is averaged, so color is weighted by 1/3. For pairs of features, color is part

of the pairing in two of three cases so when averaged across pairings, color is weighted by $2/3$. Finally, for the three features and object prime, color is weighted by 1. This weighting alone, due to averaging across conditions, could account for why 2 primed features seem better than 1, et cetera.

While the salience of the color feature may play into the effects of priming in these experiments, one can observe that it is not the sole factor in the benefit of multiple feature priming reported here. The single feature primes of motion and orientation each have an equivalent effect on performance. However, when combined into a pair (the orientation + motion prime) that pair results in significantly greater effects on performance than either of the single-feature prime (orientation or motion prime). So we can see that in cases where the color feature is not a factor, performance still derives greater benefits as the number of validly primed features increases.

Lack of Costs for Invalid Primes

In all of the priming conditions examined here (viz., Experiments 2 and 3), there were no costs observed from invalid primes. Thus, the data from these experiments seem to suggest primes can be used to benefit search performance when they are valid, without concern of harming search performance when they are invalid or irrelevant. The question is really not whether the lack of effect is real, but rather why was it revealed here when some previous research (e.g., Hailston & Davis, 2006) suggests that invalid primes do result in performance costs?

Generally speaking performance for both set sizes 2 and 4 were well above 90%. One possible explanation for the lack of costs associated with invalid primes may be the overall level of accuracy and the potential presence of ceiling effects. Maybe if overall

performance was lower, the effects of priming would be more observable. Although in the set size 8 condition performance was significantly lower than either set size 2 or 4, we still see increasing benefits of multiple feature priming and no similar costs of invalid primes.

A second possible reason for the failure to observe any effects of invalid primes is the dependent measure of interest. Perhaps if overall accuracy was lower, and response time was measured, it would be easier to pull apart negative and positive effects. Future work investigating this while controlling for speed-accuracy tradeoffs (e.g., McElree & Carrasco, 1998) is planned.

A final explanation might be the time courses involved for valid and invalid priming. Previous research (e.g., Grice & Gwynne, 1985; Hailston & Davis, 2006) has demonstrated that the effects of a prime change as the interstimulus interval (ISI) between the prime and search array varies. Hailston & Davis showed that when a search display follows a prime after a brief delay (250 ms) valid primes result in a benefit to performance while invalid primes result in performance costs, but these effects disappear following longer delays (Hailston & Davis, 2006). The ISI used in the experiments reported here was significantly shorter than the ISI reported in Hailston & Davis's work. Perhaps more time is required for invalid primes to affect search performance than required for valid primes. Future research is planned that will map out the time courses of priming to clarify exactly when and how primes affect search performance.

Practical Implications of Current Findings

In addition to performance benefits, multiple feature priming also has real practical value. We know that there are individuals who suffer from perceptual deficiencies

associated with processing one type of feature (e.g., akinetopsia and anomalous trichromacies) yet have no difficulties at all processing other types of information. For example, individuals who have red-green color vision deficits rarely have any difficulties with processing orientation or motion information. And, those with akinetopsia rarely have any problems processing orientation or color information. Thus, it should be possible to help accommodate for some perceptual deficits (such as anomalous trichromacies or akinetopsia) without harming those individuals who suffer no such deficits.

Furthermore, the reported results have implications for the design of visual displays. As discussed previously, priming can aid observers in apprehending task relevant information. One domain in which this is the case is the area of program visualization. Program visualizations are graphical representations of complex, and often dynamic information. They are used for evaluating and improving program performance, comprehending program behavior, and teaching program behavior and concepts. They follow the old adage, “a picture is worth a thousand words.” One example of a PV is the animation algorithm (AA). Animation algorithms are frequently used as instructional tools in undergraduate computer science courses to teach algorithms and data structure concepts. Ideally, they should help students grasp complex information, and obtain a better comprehension of course material, but often times this is not the case (e.g., Davis et al., 2006; Hundhausen et al., 2002; Tversky & Morrison, 2002).

Gurka and Citrin (1996) emphasized that designers must first determine what information needs to be presented and how it should be represented within the AA, so that users can apprehend it, given their perceptual and cognitive capabilities and

limitations. The AA displays often contain complex displays containing many different elements that change simultaneously as the program progresses. Given the complexity of these displays, observers may miss task relevant information by allocating their attentional resources to the “wrong” areas of the display. Priming the task relevant items in a display would aid observers in apprehending the relevant information at the appropriate times, thus increasing the overall effectiveness of AAs.

Of course, using primes to ensure apprehension of task critical information is not limited exclusively to AAs. Performance in any task involving visual displays (e.g., air traffic control, nuclear power plants, airport security screening, etc.) could derive benefits from the use of priming.

Comparing Theoretical Predictions

One purpose of the experiments reported here was to compare three prominent theories of visual attention to see which best predicted performance in feature search vs. simple, triple-conjunction search. Experiment 1 was specifically designed for this purpose. Recall in this experiment each distractor shared one and only one feature with the target stimulus. Designing the experiment this way allowed for a direct comparison with the predictions made by both the Guided Search and the Multidimensional Signal Detection Model.

Additionally, the models were intuitively extended to see how well each might account for priming effects in cases where distractors share either one or two features with a target (viz. Experiments 2 and 3). It is easier to extend both PLT and GS than it is MSDM. Eckstein and his colleagues (Eckstein et al., 2000) offer us predictions about how performance trends would look in these cases. Performance would be much worse

in cases where distractors share two features with a target stimulus than when only one feature is shared with the target. However, the problem arises when one considers how priming would affect performance.

The predictions made by each modified model and how they compare to the data obtained are discussed below. In short, in their current forms none of the three models is able to account for all of the obtained data in the current experiments. In Experiment 1 (where the design employed allowed for direct comparisons) PLT failed to account for any of the obtained results, while both GS and MSDM were able to account for some but not all. In Experiments 2 and 3, the intuitively modified versions of both PLT and GS failed to accurately account for observed performance of priming effects. MSDM was not compared in these last two experiments due to the reason mentioned above.

Perceptual Load Theory

Perceptual Load Theory would predict that priming the perceptual system to specific features would reduce the range of features necessary for focus, or in effect broadening the area of illumination under the spotlight of attention. This would decrease the amount of resources necessary to process stimuli, and lead to observed benefits in performance, much like those observed. The same would be true with invalid primes. In these cases the area of illumination would still be broadened (i.e., the perceptual system is still primed), additional resources would still be available for processing, and as a result we should see some degree of benefit even for invalidly primed targets (although the degree of benefit would likely be less than for valid primes). However, there was neither an observable benefit or cost in the data reported here.

Alternatively, it may be the case that priming would increase the perceptual load of the observer simply by presenting more information for processing. This would further constrain the area of illumination under the spotlight of attention, and reduce the amount of attentional resources available for processing. If this were the case, then we would still expect to see some performance benefits on validly primed trials, as we did, but we also would expect to see symmetrical costs associated for performance on invalidly primed trials, which we did not.

In both Experiments 2 and 3 we observed no effect of invalid primes. Thus, neither of these predictions from the modified PLT accurately predicts the data obtained from the current experiments. In its current form, PLT fails to accurately predict the observed data in any of the three experiments conducted in this study.

Guided Search

Recall that, GS predicts relatively equal performance between single feature and simple, triple-conjunction searches when each distractor shares only one feature with the target stimulus. This is what we observed in the color feature and simple, triple-conjunction search conditions in Experiment 1. However, performance in the triple conjunction search was significantly better than performance in both the orientation and motion feature search. Thus, GS does not accurately predict performance in either of these cases.

The GS model also falls short when it is intuitively extended to predict performance associated with priming in both Experiment 2 and 3. In these cases we can intuitively make either of two possible predictions, based on the model modifications.

First, since the primes in this case offered no reliable information about the likelihood of which target was to appear (recall prime was equally likely to be valid or invalid on any given trial), we can assume they offer no additional top-down weighting (based on expectancies placed by the presentation of a prime) to the differences in bottom-up saliencies of items. Thus, performance would be based solely on the salience differences present in the search display, and we would see no effects at all of priming. Given we did observe a benefit of valid primes, this prediction can not be correct.

A second possible prediction made by the modified GS model is that the presentation of a prime stimulus does indeed modulate the bottom-up salience differences of the activation map. In this case, we would expect to see performance benefits associated with valid primes which would increase as the number of validly-primed features increases. This is exactly what we observe in both Experiments 2 and 3. However, we would also expect to see a similar trend in costs associated with negatively-primed features. Given we see no costs associated with negative primes, this prediction also proves to be incorrect.

Multi-dimensional Signal Detection Theory Model

Recall that, MDSM predicts better performance in triple-conjunction searches, where distractors share only one feature with a target than it does for simple feature searches. This prediction agrees with what was observed in Experiment 1 when either the orientation or motion feature search was compared with the triple-conjunction search. However, the predictions made by MSDM did not hold when the color feature search was compared to the triple-conjunction search in Experiment 1.

As previously mentioned, MSDM would predict significantly worse performance (i.e., large set-size effects) in cases where distractors share more than one feature with the target stimulus. We observed significant set-size effects in both Experiments 2 and 3.

The data obtained from the current experiments does not allow one to make any statements about how well MSDM does in accounting for priming effects when distractors share more than one feature with the target stimulus. This is because the current experiments do not clarify exactly how these priming effects work. It is impossible to differentiate between cases of signal enhancement (i.e., primes make the target stimulus more salient), external noise reduction (i.e., primes decrease the saliency of distractors), and internal noise reduction (i.e., primes suppress activation of invalid feature channels). Until we can differentiate among these three possible effects of primes, we can not extend MSDM to account for priming effects. Future research is planned that will address and differentiate among these possibilities.

Future Directions

The supremacy of color is one powerful trend that spanned all three experiments. Color may have been the most salient and, therefore, most relied upon feature of the three examined. However, it may also be a result of the design used in the current experiments, as described below. Additionally it may be that color is an intrinsic (i.e., non-separable) property of a stimulus whereas other features (e.g., orientation and motion) are not (Wolfe, 1998). If this is the case, then even though color is processed quasi-independently of orientation and motion, it might not be perceptually separable from the object itself.

The values used for all three features examined in these experiments were polar opposites – red vs. green, vertical vs. horizontal, and left vs. right movement. Although logically it seems that the differences between each pole were roughly equivalent for all three features, it may not have been the case. Perhaps the perceptual difference between red and green is greater than either vertical vs. horizontal, or left vs. right motion. Future research is planned to psychophysically equate the perceptual discriminability of the three features, to ensure that the perceptual differences between values are equal. Moreover, one can then systematically change the discriminability (or confusability) of each feature. For example, using red versus orange should be less discriminable (or more confusable) than red versus green colors. Doing this may also allow more rigorous, quantitative testing of models, such as the MDSM model. This will offer a clearer picture as to the salience of the individual feature primes.

Finally, future research is planned that will examine the effects using other features in multiple-feature priming. Wolfe and Horowitz (2004) listed several features that might guide the deployment of attention. They group these features by the likelihood of their ability to influence attentional deployment. Among these are features such as size, luminance, curvature, and aspect ratio. In all they list 29 different features. Each of these can be tested using an improved version of the current paradigm to examine its respective salience as well as the effects of simultaneously priming that feature with combinations of other features. Doing so may help to distinguish the best features to prime (i.e., have the greatest benefits to performance), and whether the efficiency of these features change under different conditions. This information will aid designers in ensuring that observers are best able to apprehend information in their displays.

Concluding Remarks

In summary the data from the reported experiments offer the following information. First, valid primes do benefit performance. Second, although color appeared to drive performance in all three experiments, it is still the case the priming more features can result in additional benefits. This can be seen in cases where motion and orientation were both primed. The resulting benefits were larger than when either of the two was primed by itself, although neither was more salient than the other when tested alone. Thus, designers can help improve users' performance by using primes, and priming multiple relevant feature dimensions in their displays. Finally, in their current forms, none of the three models discussed in this dissertation can accurately account for performance in all tested conditions. This suggests that each requires some modification, and future research is planned to investigate how best to modify each.

APPENDIX A

EFFECTS OF INVALID PRIMES IN TRIPLE-CONJUNCTION SEARCH

As mentioned in the results section of Experiment 2, no performance costs were associated with invalid primes. The following are the results of the analyses conducted on the invalid prime data from Experiment 2.

Single Feature Primes

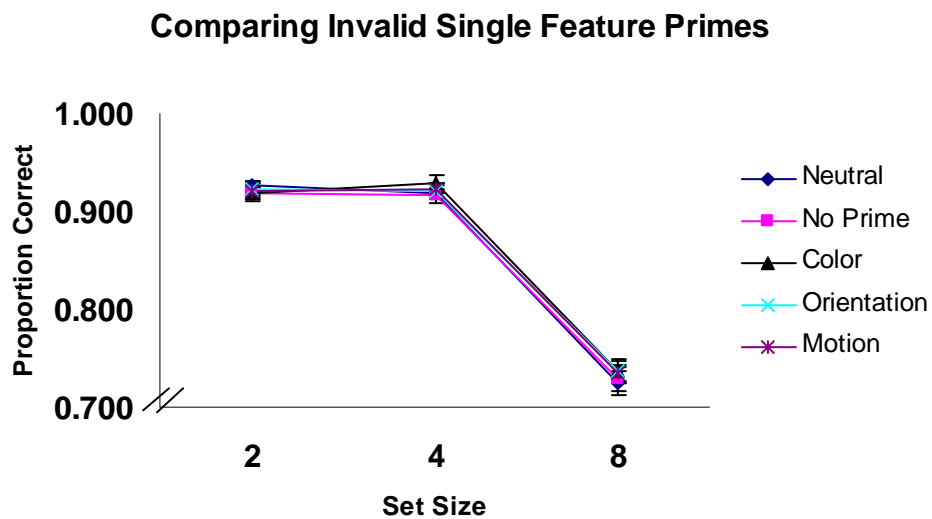


Figure 12. Comparison of invalid single feature, neutral, and no prime conditions. Error bars represent ± 1 SEM.

Repeated measures ANOVAs were conducted to compare each single feature prime to the neutral prime and to each of the other two single feature primes. Table 8 lists the results of these ANOVAs.

Table 8

Single Feature Primes vs. Neutral and Other Features

| Comparison | $F(1,23)$ | p value |
|-----------------------|-----------|-----------|
| Color - Neutral | 0.093 | 0.763 |
| Orientation - Neutral | 0.021 | 0.886 |
| Motion - Neutral | 0.004 | 0.953 |
| Color - Orientation | 0.054 | 0.818 |
| Color - Motion | 0.310 | 0.583 |
| Orientation - Motion | 0.048 | 0.829 |

Comparing Paired Feature Primes

Comparing Invalid Paired Feature Primes

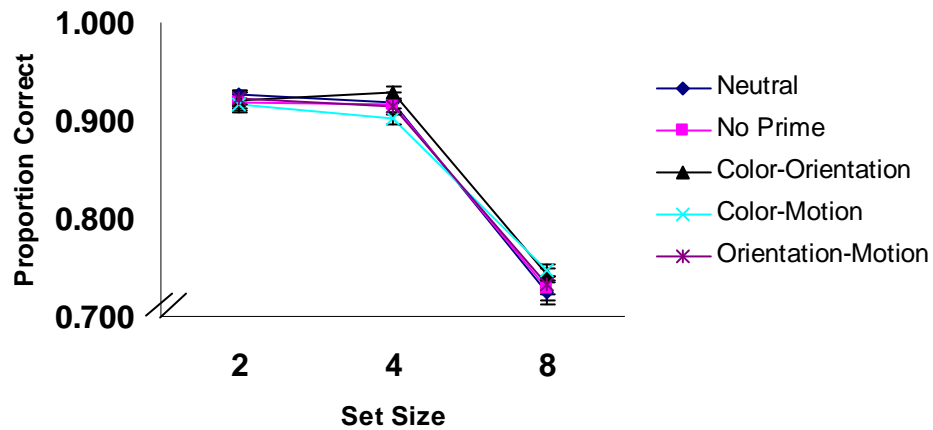


Figure 13. Accuracy performance for invalid paired feature primes plotted as a function of set size. Error bars represent ± 1 SEM.

The comparison of invalid paired feature primes also revealed no effects of primes.

Table 9 lists the results of repeated-measures ANOVAs comparing the paired feature primes against one another.

Table 9

| <i>Comparison of Invalid Paired Feature Primes</i> | | |
|--|-----------|-----------|
| Comparison | $F(1,23)$ | p value |
| Color-Motion/Color-Orientation | 3.300 | 0.066 |
| Color-Motion/Orientation-Motion | 2.025 | 0.168 |
| Color-Orientation/Orientation-Motion | 0.216 | 0.646 |

Effects of Invalid Multiple Feature Primes

A 3 by 3 repeated-measures ANOVA was conducted. The two factors were priming condition (1 vs. 2 vs. 3 features) and set size (2, 4, and 8). This ANOVA revealed a significant main effect of set size ($F(2,46) = 550.515$; $p < 0.001$). There was no effect of priming condition ($F(2,46) = 0.320$; $p = 0.728$) and no significant interaction.

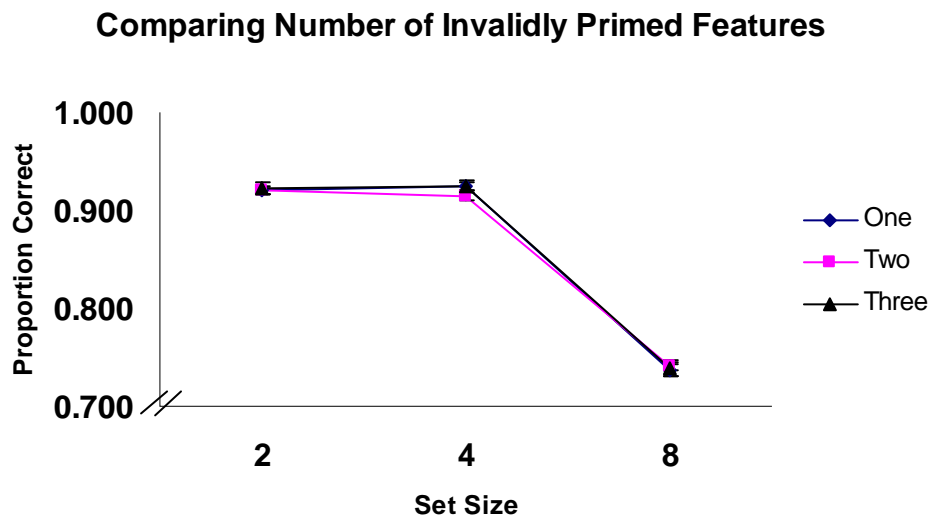


Figure 14. Accuracy levels for varying priming conditions plotted as a function of set size. Error bars represent ± 1 SEM.

APPENDIX B

EFFECTS OF INVALID PRIMES IN WHOLE-OBJECT SEARCH

Similar to the results of Experiment 2, the data from Experiment 3 revealed no significant effects on performance resulting from invalid primes. The following are the results of the analyses conducted on the invalid prime data from Experiment 3.

Single Feature Primes

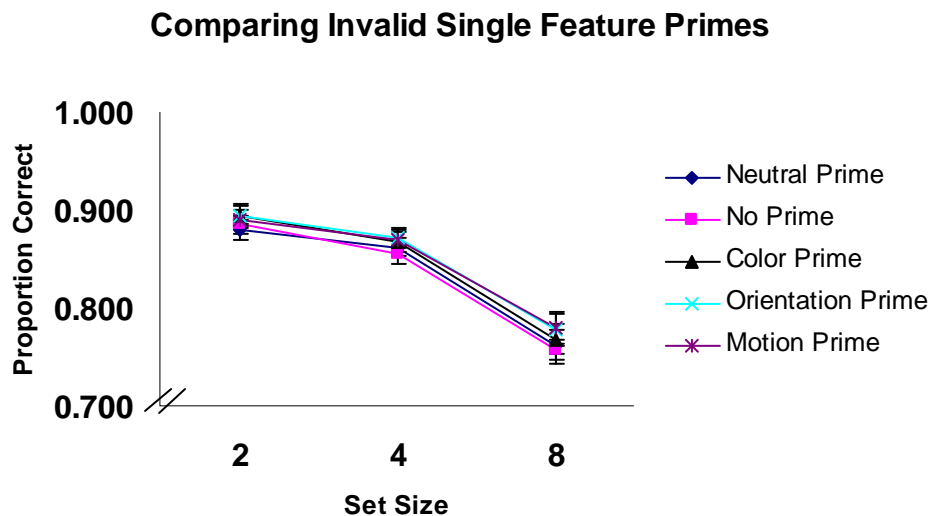


Figure 15. Comparison of invalid single feature, neutral, and no prime conditions. Error bars represent ± 1 SEM.

Repeated measures ANOVAs were conducted to compare each single feature prime to the neutral prime and to each of the other two single feature primes. Table 10 lists the results of these ANOVAs.

Table 10

| <i>Single Feature Primes vs. Neutral and Other Features</i> | | |
|---|-----------|-----------|
| Comparison | $F(1,23)$ | p value |
| Color - Neutral | 1.973 | 0.173 |
| Orientation - Neutral | 0.304 | 0.739 |
| Motion - Neutral | 2.001 | 0.097 |
| Color - Orientation | 0.320 | 0.577 |
| Color - Motion | 0.107 | 0.747 |
| Orientation - Motion | 0.037 | 0.849 |

Comparing Paired Feature Primes

Comparing Invalid Paired Feature Primes

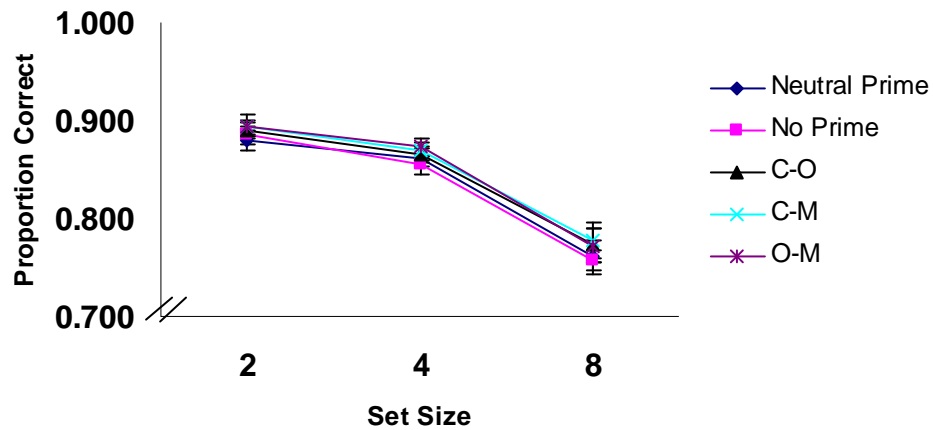


Figure 16. Accuracy performance for invalid paired feature primes plotted as a function of set size. Error bars represent ± 1 SEM.

The comparison of invalid paired feature primes also revealed no significant effects of primes. Table 11 lists the results of repeated-measures ANOVAs comparing the paired feature primes against one another.

Table 11

| <i>Comparison of Invalid Paired Feature Primes</i> | | |
|--|-----------|-----------|
| Comparison | $F(1,23)$ | p value |
| Color-Motion/Color-Orientation | 0.238 | 0.630 |
| Color-Motion/Orientation-Motion | 0.149 | 0.703 |
| Color-Orientation/Orientation-Motion | 0.001 | 0.982 |

Effects of Invalid Multiple Feature Primes

A 3 by 3 repeated-measures ANOVA was conducted. The two factors were priming condition (1 vs. 2 vs. 3 features) and set size (2, 4, and 8). This ANOVA revealed a significant main effect of set size, $F(2,46) = 233.693$; $p < 0.001$. There was no effect of priming condition $F(2,46) = 2.190$; $p = 0.112$. Furthermore, there were no significant interaction revealed.

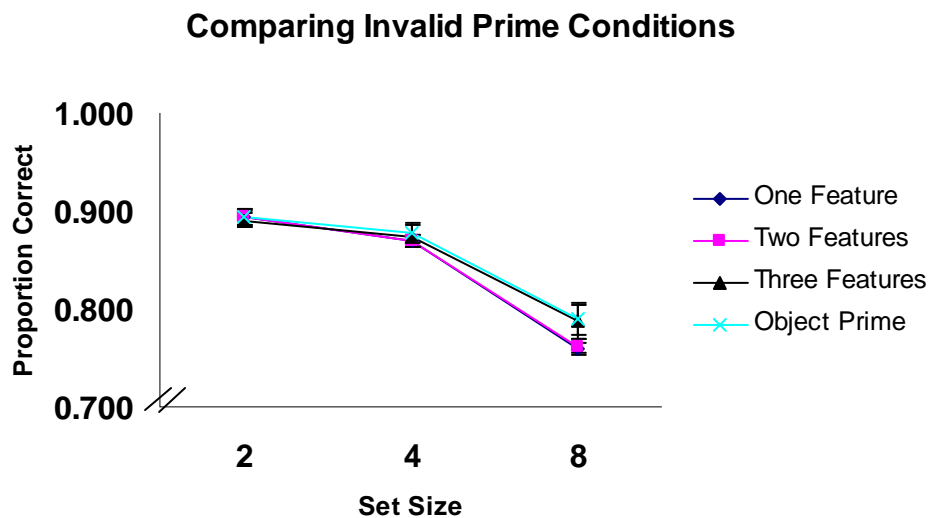


Figure 17. Accuracy levels for varying priming conditions plotted as a function of set size. Error bars represent ± 1 SEM.

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