Available online at www.sciencedirect.com
ScienceDirect
Vision Research 46 (2006) 4083–4090
Vision Research
www.elsevier.com/locate/visres

# Detection of multidimensional targets in visual search

Patrick Monnier *

*Department of Psychology, Colorado State University, Fort Collins, CO 80523-1876, USA*

Received 1 February 2006; received in revised form 27 July 2006

**Abstract**

Search performance for targets defined along multiple dimensions was investigated with an accuracy visual search task. Initially, threshold was measured for targets that differed from homogeneous distractors along a single dimension (e.g., a reddish target among achromatic distractors, or a right-tilted target among vertically oriented distractors). Threshold was then measured for a multidimensional target (a redundant target) that differed from homogeneous distractors along two dimensions (e.g., a reddish AND right-tilted target among achromatic, vertically oriented distractors). Search performance for multidimensional target combinations of chromaticity and luminance, chromaticity and orientation, and chromaticity and spatial frequency was tested. Measurements were evaluated within several summation models, allowing for a test of the mechanisms mediating the detection of multidimensional targets in search. Measurements were generally consistent with probability summation suggesting the particular combinations of stimulus dimensions tested were coded along independent, noisy, neural mechanisms.


*Keywords:* Visual search; Multidimensional target; Redundant coding; Summation; Probability summation

## 1. Introduction

Looking for a set of keys on a crowded desktop or searching for a book on a bookshelf are examples of visual search. Intuitively, some searches are easy and fast, while others are hard and slow. At the risk of trivializing, one can say that much of research dealing with visual search since Treisman's seminal work (Treisman & Gelade, 1980) has been aimed at understanding this difference. The concept that is often invoked to account for fast and slow searches is that visual attention is a process with limited capacity. When a particular search does not exceed the limit in attention capacity, the search is easy and fast. When a search exceeds the limit in attention capacity, the search is difficult and slow. This view was originally formalized in Treisman's model of visual search: fast searches (usually simple-feature searches) are processed pre-attentively, and hence in parallel, while hard searches (usually conjunction searches) require focused attention, a slow, serial process (Treisman & Gelade, 1980). Several current models of visual search have preserved these two basic components, though the models differ in detail (e.g., Treisman & Gelade, 1980; Wolfe, 1994).

Another commonly adopted principle in search is that visual information is processed through multiple sequential stages. At the earliest stage, peripheral feature detectors extract basic object characteristics such as color, size, orientation, depth, etc. Signals from these detectors are combined at a later stage to form an object representation. In search, these neural signals must ultimately be compared to decide whether a target is present.

This brief summary may misleadingly suggest that most questions in this area of research have been resolved. To the contrary, even basic issues such as what constitutes the peripheral feature detectors of the early stage of search, remain unanswered. Some (e.g., Treisman & Sato, 1990; Verghese, 2001; Wolfe, 1994) have adopted the physiological building blocks of vision (i.e., Hubel & Wiesel, 1968; Livingstone & Hubel, 1988) in the form of retinotopic filters tuned to basic visual characteristics (chromaticity, orientation, spatial frequency, etc.). Others have questioned

* Fax: +1 970 491 1032.
*E-mail address:* patrick.monnier@colostate.edu

0042-6989/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.visres.2006.07.032

this parallelism with basic visual processing (e.g., Shimozaki, Eckstein, & Abbey, 2002; Wolfe, 2003). Lending support to the latter view is psychophysical evidence showing basic feature detectors of search exhibit tuning characteristics that are often broader than the peripheral visual mechanisms identified with threshold paradigms. For example, critical color differences tend to be much larger for visual search than just noticeable differences estimated with color discrimination. Moreover, a supra-threshold color representation cannot be derived simply (Bauer, Jolicœur, & Cowan, 1998; Carter & Carter, 1981; Nagy & Sanchez, 1990). Furthermore, it may be that feature detectors mediating search are not tuned to a single dimension but that they may be simultaneously selective for multiple dimensions. Supporting this view is physiology showing that a significant number of cells as early as in V1 (Leventhal, Thompson, Liu, Zhou, & Ault, 1995) and V2 (Gegenfurtner, Kiper, & Fenstemaker, 1996) are simultaneously selective for multiple visual attributes (e.g., color and orientation, or color and direction of motion).

The present study examined the low-level feature detectors subserving search for relatively simple displays. In particular, search performance was measured for targets that differed from a homogeneous set of distractors along two dimensions (e.g., targets that differed from distractors both in chromaticity and orientation). Specifically, I tested whether a multidimensional target that differed from homogeneous distractors was more detectable than a unidimensional target that differed from distractors along either dimension alone. The measurements were assessed within several models of summation that are described next.

### 1.1. Quantitative approach

The most commonly used dependent variable in studies of visual search is reaction time. An alternative dependent variable is response accuracy in which a stimulus display is presented as a brief flash and response accuracy is measured as a function of the target-to-distractor difference. Typically, several target-to-distractor difference levels are tested spanning a wide range of search accuracy performance. From the obtained psychometric function, a threshold representing the target-to-distractor difference necessary to reach criterion performance is estimated. One advantage of the search accuracy task is that it allows for the adaptation of quantitative models of visual attention developed within signal detection theory (Palmer, 1994; Palmer, Ames, & Lindsey, 1993; Palmer, Verghese, & Pavel, 2000; Verghese, 2001).

According to the signal detection approach, each element in a search display is presumed to result in an internal representation that can be characterized by a single number. Furthermore, such a response is assumed to be variable and this variability is described by a probability distribution (this assumption satisfies the fact that biological systems are inherently noisy so that the presentation of a stimulus of fixed intensity will result in a variable neural response). The simplest model (the one adopted here) is that the shape of this probability distribution is normal and that the distributions that characterize a distractor and a target have equal variance (the target and distractor distributions are identical in shape). The mean of the distribution is the average value or average strength of the internal representation and the standard deviation of the distribution represents the variability of the internal representation. The probability distributions for the target and distractors are shifted along the relevant dimension (e.g., chromaticity if the target differs from the distractors in chromaticity) by an amount proportional to the target-to-distractor difference. At the decision stage, the signal producing the largest response is selected to be the target (maximum rule). Because of the variability of the internal representations, a distractor will sometimes be mistaken for a target (a type of error called a false alarm) and a target will sometimes be mistaken for a distractor (a type of error called a miss).

One critical implication of this approach is that because in most visual search experiments multiple distractors are presented, error rates will be proportional to the number of distractors. That is, as set size increases, search performance deteriorates as errors due to the noisy representation of multiple elements will accumulate. This modest deterioration in performance with set size is referred to as a decision phenomenon since the quality of the internal representations remains unchanged (only the number of representations and hence the error rates, change). Quantitative calculations of the slope relating performance to the number of elements (set size) suggest a modest but significantly greater than zero slope (the magnitude of the predicted slope depends on several factors such as the type of task, and assumptions about decision rules and underlying distributions [see Palmer et al., 2000]). One of the implications of this approach is that positive set size slopes cannot necessarily be interpreted as evidence for a limit in attention capacity.

In the present study, these principles of signal detection were used in conjunction with three summation models to determine the nature and number of the neural mechanisms underlying search for multidimensional targets. Originally, the summation models were developed to determine the number of neural mechanisms subserving spatial frequency detection (e.g., Graham, 1977; Graham & Nachmias, 1971). In general, the approach is to compare visual performance for a "compound" stimulus to performance for the components of the compound. If the components are detected by a single neural mechanism, the compound stimulus should show significant summation and be much more detectable than the components. If, on the other hand, the components are detected by independent mechanisms, the compound may not be much more detectable than either component alone (See Graham, 1989 for quantitative development of the approach). This approach is ideally suited for the question at hand: How much more detectable are multidimensional targets and what are the underlying mechanisms mediating search for such target?

### 1.2. Summation predictions

Search performance in the present study was assessed within summation-square plots (Graham, 1989; Graham, Robson, & Nachmias, 1978). In such a plot (Fig. 1), the orthogonal dimensions represent the relative intensity of two components assumed to be detected by independent mechanisms. For example, the $x$-axis and $y$-axis could represent the chromatic difference and spatial frequency difference between the target and distractors, respectively. Diagonals (dashed lines in Fig. 1) represent the relative intensity of multidimensional targets that differ from the distractors along both dimensions (e.g., both in chromaticity and spatial frequency).

Because search performance for the two dimensions is not directly comparable, the stimulus space has to be normalized in the following way. Initially, indices of detectability representing 75% thresholds ($d' = 1.34$) are estimated for each dimension (orthogonal axes in Fig. 1). These thresholds are subsequently used to normalize the stimulus space. Multidimensional targets are then generated in the normalized space along diagonal directions representing different target ratios of the two dimensions (dashed lines in Fig. 1). The 35°, 45°, and 55° diagonal directions represent multidimensional targets with dimension ratios of 1.43, 1.0, and 0.70, respectively. Indices of detectability representing 75% thresholds ($d' = 1.34$) are then estimated along these diagonals (see below for detail). Since the normalization is done for each observer and for each set size level, each observer was presented with slightly different multidimensional targets.

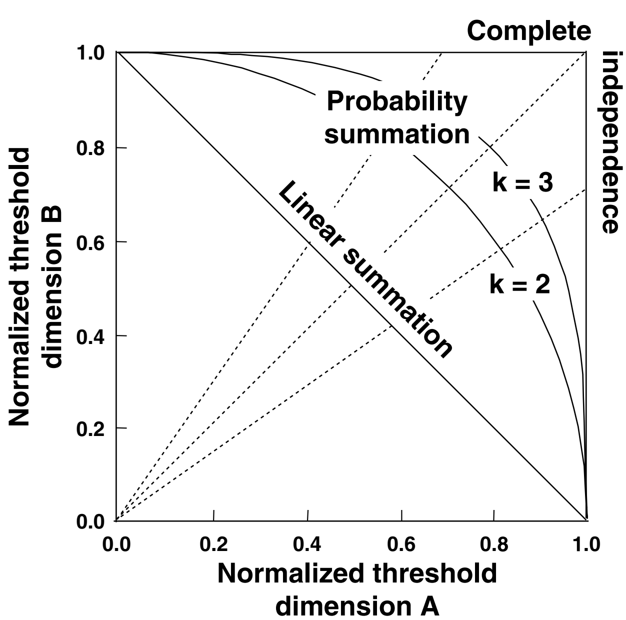


Fig. 1. Summation-square plot and three classes of summation predictions for multidimensional targets: complete independence (outer-most contour), linear summation (diagonal line with negative unity slope) and probability summation (curved contours assuming two levels of probability summation; see text for detail).

If multidimensional targets are detected by two sets of detectors, each independently encoding one dimension, the target-to-distractor difference should be large enough so that either or both detectors are at threshold (the outmost contour labeled "complete independence" in Fig. 1). If multidimensional targets are detected by neural units simultaneously tuned to both dimensions, multidimensional thresholds should fall near the diagonal line with negative unity slope labeled "linear summation". For example, a multidimensional target composed of an equal proportion of both dimensions (45°) will reach criterion performance at half the normalized unidimensional threshold since signals from both mechanisms linearly sum ($0.5 + 0.5 = 1.0$). Finally, if multidimensional targets are detected by independent, but noisy neural mechanisms, multidimensional thresholds should fall near the curved contours labeled "probability summation". The amount of probability summation can be estimated by the slope of the psychometric function (e.g., Graham, 1989; Mortensen, 2002; Quick, 1974). The probability summation contour is obtained using the following equation:

$$1 = A^k + B^k \quad (1)$$

where $A$ and $B$ are normalized signal strength for dimensions $A$ and $B$, and $k$ is the slope of the psychometric function. The larger the value of $k$, the closer the probability summation contour will be to the complete independence contour. The smaller the value of $k$, the closer the probability summation contour will be to the linear summation contour. Conceptually, a steep psychometric function is the signature of an underlying mechanism with little noise. A multidimensional target detected by two independent mechanisms with little noise would result in little probability summation as the likelihood of either or both mechanisms to be in a detect state below threshold is relatively low. On the other hand, a shallow psychometric function is indicative of a mechanism with high noise. If detection is mediated by two such high noise mechanisms, probability summation will be more likely as the probability of either or both mechanisms to be in a detect state below threshold is more likely. Two commonly obtained probability summation contours shown in Fig. 1 represent slopes of $k = 2$ and $k = 3$.

An additional assumption that applied to all three models of summation is that observers have the ability to simultaneously monitor the appropriate number of channels without reaching a limit in attention capacity. For example, in the multidimensional conditions, it is assumed that observers are monitoring both feature channels making up the multidimensional target, at all spatial locations.

## 2. Methods

### 2.1. Observers

Three observers took part in the study (only two in Experiment 3) and were between 22 and 35 years of age. Observers D.R. and G.M. were volunteer students enrolled in the Honors College at Florida Atlantic University. D.R. was a naïve observer and P.M. is the author. Observers had normal or corrected acuity (20/20) and tested normal for color vision (Ishihara plates). Observers underwent multiple practice sessions before data collection. Each subject gave written informed consent and the study was approved by an Institutional Review Board at Florida Atlantic University.

### 2.2. Apparatus and calibration

Stimuli were displayed on a 17 in. CRT monitor (Eizo FlexScan T566, $1152 \times 870$ pixels, 75 Hz). A Macintosh G4 equipped with a ATI Radeon 7000 video card (10 bits per gun) was used to generate and present stimuli.

The spectral power distribution of the three guns was measured using a Photo Research PR-650 spectroradiometer. Each gamma function was sampled at 16 locations, separated by equal intervals. The entire function was interpolated using the 16 sample measurements. The gamma corrections were stored in a look-up table in the computer. Calibration was regularly checked with the spectroradiometer.

Chromaticities were specified in a cone-based color space (MacLeod & Boynton, 1979) where the $x$- and $y$-axes represent chromaticities producing differential activity only in the L–M and S color-opponent mechanisms, respectively. Furthermore, the axes were normalized by luminance [i.e., $l = \mathrm{L}/(\mathrm{L}+\mathrm{M})$ and $s = \mathrm{S}/(\mathrm{L}+\mathrm{M})$]. In this color space, the unit of $s$ is arbitrary and was normalized to one for equal-energy white (EEW).

### 2.3. Stimuli and procedure

Visual search performance was measured using a yes–no accuracy visual search task. Data collection took place in a darkened room. A block of trials consisted of 10 target present practice trials, followed by 100 experimental trials. Within a block of 100 randomly presented trials, 50 contained a target and 50 contained no target. For each condition, six to eight levels of target-to-distractor differences were tested in different blocks of trials. Hit and false alarm rates at each stimulus level were converted to an index of detectability ($d'$). A target-to-distractor stimulus difference representing 75% detection performance ($d' = 1.34$) was extrapolated from a straight line fit to 6–8 indices of detectability. Each threshold was therefore estimated using 300–400 trials. Set sizes of 2 and 8 elements were tested.

Search performance was first measured for unidimensional targets that differed from the distractors along a single dimension (unidimensional targets; e.g., color only OR luminance only). These unidimensional thresholds were used to normalize the stimulus space and generate targets that differed from the distractors along both dimensions (e.g., color AND luminance). The normalization was necessary to compare performance for search along otherwise incomparable dimensions. Furthermore, the normalization allowed for the generation of multidimensional targets with specific ratios of the two dimensions, expressed in units of detectability. Multidimensional thresholds were measured along three diagonal directions in the normalized space: 35°, 45°, and 55°. As the normalization was done individually, each observer was presented with slightly different multidimensional targets.

## 3. Results

### 3.1. Experiment 1: Chromaticity and luminance targets

Target and distractors were Gaussian blobs (standard deviation: 0.1425°) and were presented in a circular region measuring 2.3° in diameter, centered on a dark fixation point. Elements were separated by about 0.40° and independently jittered by ±0.18° (randomly selected from a uniform distribution). Target and distractors were presented on an achromatic background roughly metameric to EEW ($l$, $s$, $Y$: 0.66, 1.0, and 12 cd/m$^2$). Initially, thresholds were measured for targets that differed from the distractors in either chromaticity ($l$-increment, which appeared reddish) or in luminance (luminance increment from the distractors). The chromaticity of the distractors appeared achromatic ($l$, $s$, $Y$: 0.66, 1.0, and 20 cd/m$^2$) and was a luminance increment from the achromatic background ($l$, $s$, $Y$: 0.66, 1.0, and 12 cd/m$^2$). Multidimensional thresholds were measured along three diagonal directions in the normalized space (Fig. 1).

Table 1 lists unidimensional difference thresholds for each experiment, each observer, and set size 2 and 8 separately. Fig. 2 shows threshold measurements for three observers in summation-square plots. The $x$- and $y$-axes represent normalized $l$-chromaticity and normalized luminance, respectively. The contours are the various summation predictions, as shown in Fig. 1. Solid circles and open squares are set size 2 and 8 thresholds, respectively. Error bars represent the standard error of the mean of two independent threshold estimates. Multidimensional thresholds generally fell closer to the probability summation or to the complete independence contours than the linear summation contour, although there was quite a bit of variability within and across observers. Table 2 lists the calculated RMS prediction errors for each model, the within variance (measurement error), and the ratio expressing the prediction squared error compared to the within variance. The quantities were average across observers and set size. A ratio of one would indicate that the model predicts the data within measurement error. The ratios for the two probability summation models were near one and were at least two times smaller than the linear summation and complete independence models' ratios.

Table 1
Difference thresholds for unidimensional targets for each experiment, each observer and set 2 and 8

| | Set size 2 | | Set size 8 | |
|---|---|---|---|---|
| Experiment 1: chromaticity and luminance | | | | |
| | $l$ | Lum | $l$ | Lum |
| DR | 0.0059 | 2.38 | 0.0099 | 3.98 |
| GM | 0.0050 | 3.06 | 0.0056 | 4.65 |
| PM | 0.0057 | 4.30 | 0.0076 | 6.78 |
| Experiment 2: chromaticity and orientation | | | | |
| | $l$ | Deg | $l$ | Deg |
| DR | 0.0102 | 11.84 | 0.0175 | 23.22 |
| GM | 0.0059 | 16.79 | 0.0069 | 23.54 |
| PM | 0.0069 | 14.00 | 0.0097 | 19.88 |
| Experiment 3: chromaticity and spatial frequency | | | | |
| | $l$ | SF | $l$ | SF |
| GM | 0.0050 | 0.24 | 0.0052 | 0.31 |
| PM | 0.0047 | 0.31 | 0.0060 | 0.48 |

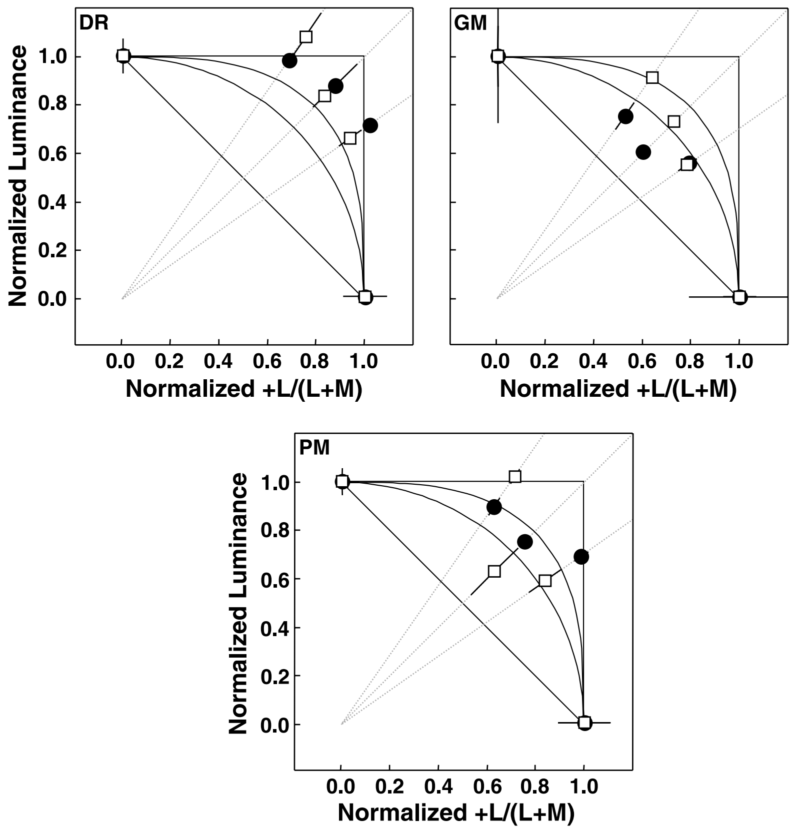


Fig. 2. Experiment 1: summation-square plots showing thresholds for multidimensional targets that were Gaussian blobs and differed from the homogeneous distractors in both chromaticity and luminance. Solid circles and open squares are set size 2 and 8 thresholds, respectively. Error bars represent the standard error of the mean of two independent threshold estimates.

Table 2
RMS prediction errors (first column), within variance (second column) and the ratio of these two quantities (third column), calculated for each experiment and each model, averaged across observers and set size

| RMS prediction errors and within variances | $\sum(x_i - \hat{x})^2$ | $\sum(x_i - \bar{x})^2$ | $\frac{\sum(x_i-\hat{x})^2}{\sum(x_i-\bar{x})^2}$ [a] |
|---|---|---|---|
| Experiment 1 | | | |
| Linear summation | 2.807 | 0.327 | 8.584 |
| Prob. Sum. $k = 2$ | 0.487 | 0.327 | 1.489 |
| Prob. Sum. $k = 3$ | 0.373 | 0.327 | 1.141 |
| Complete independence | 1.255 | 0.327 | 3.838 |
| Experiment 2 | | | |
| Linear summation | 2.967 | 0.098 | 30.276 |
| Prob. Sum. $k = 2$ | 0.363 | 0.098 | 3.704 |
| Prob. Sum. $k = 3$ | 0.133 | 0.098 | 1.357 |
| Complete independence | 0.742 | 0.098 | 7.571 |
| Experiment 3 | | | |
| Linear summation | 1.439 | 0.153 | 9.405 |
| Prob. Sum. $k = 2$ | 0.184 | 0.153 | 1.203 |
| Prob. Sum. $k = 3$ | 0.203 | 0.153 | 1.327 |
| Complete independence | 1.010 | 0.153 | 6.601 |

[a] A ratio near one indicates that the model predicts the data within measurement error.

### 3.2. Experiment 2: Chromaticity and orientation

Target and distractors were elongated Gaussian blobs (standard deviations: 0.1425° by 0.0713°) and were presented in a circular region measuring 2.3° in diameter, centered on the dark fixation point. Elements were separated by 0.40° and independently jittered by ±0.18° (randomly selected from a uniform distribution). Target and distractors were presented on an achromatic background roughly metameric to EEW ($l$, $s$, $Y$: 0.66, 1.0, and 12 cd/m$^2$). Thresholds were first measured for targets that differed from the distractors in chromaticity only ($l$-increment, which appeared reddish) and in orientation only (tilted right). The distractors were always vertically oriented and appeared achromatic ($l$, $s$, $Y$: 0.66, 1.0, and 20 cd/m$^2$). Fig. 3 shows threshold measurements for three observers in summation-square plots. Format is identical to Fig. 2, except that the $y$-axis is normalized orientation. Multidimensional thresholds were generally closer to the probability summation contours than either the complete independence or the linear summation contour. This was consistent for all three observers. Furthermore, there did not appear to be differences between set size 2 and 8. The probability summation models' superiority was confirmed by the ratios expressing the prediction squared error compared to the within variance (Table 2). The ratios for the two probability summation models were two to twenty-two times smaller than the linear summation and complete independence models' ratios. In this experiment, the probability summation model

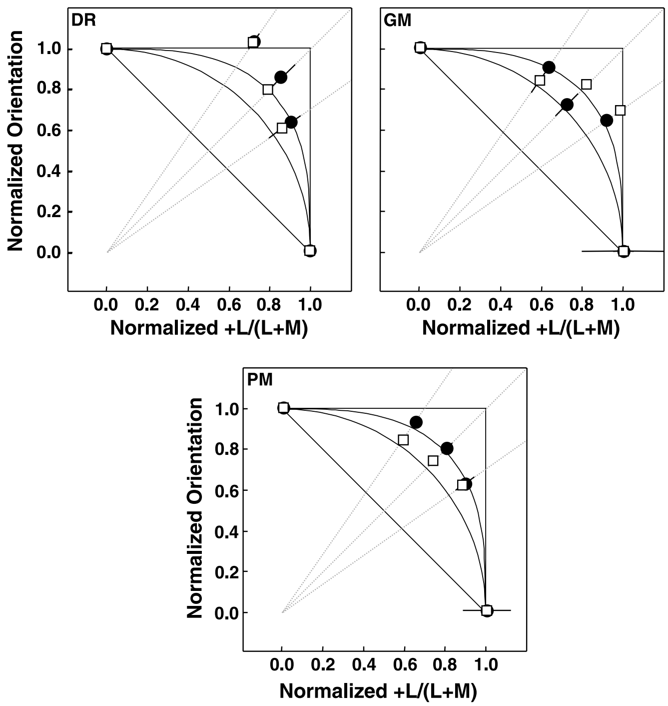


Fig. 3. Experiment 2: summation-square plots showing thresholds for multidimensional targets that were elongated Gaussian blobs and differed from the homogeneous distractors in both chromaticity and orientation. Format and symbols identical to Fig. 2.

with a $k = 3$ was superior to the probability summation model with a $k = 2$.

### 3.3. Experiment 3: Chromaticity and spatial frequency

Target and distractors were vertical Gabor patches (standard deviation: 0.375°) presented in a circular region subtending 9.0° in diameter, centered on the dark fixation point. Elements were separated by about 3.5° and independently jittered by ±0.5° (randomly selected from a uniform distribution). Thresholds were first measured for targets that differed from the distractors only in chromaticity (*l*-increment, which appeared reddish) and in spatial frequency only (higher spatial frequency relative to the distractors). The distractors were vertically oriented and appeared achromatic (*l*, *s*, *Y*: 0.66, 1.0, and 20 cd/m$^2$) at a spatial frequency of 1.5 cycles per degree. Fig. 4 shows normalized thresholds for two observers (observer D.R. did not participate in this experiment) in summation-square plots. Format is identical to Fig. 2, except that the *y*-axis is normalized spatial frequency.

Multidimensional thresholds were generally closer to the probability summation contours compared to the complete independence and linear summation contours. Further, there was no clear difference between set size 2 and 8 thresholds. The probability summation model's superiority was confirmed by the ratios expressing the prediction squared error compared to the within variance (Table 2). The ratios for the two probability summation models were

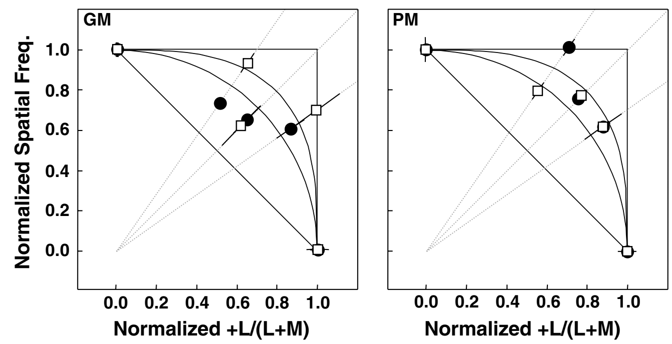


Fig. 4. Experiment 3: summation-square plots showing thresholds for multidimensional targets that were Gabors and differed from the homogeneous distractors in both chromaticity and spatial frequency. Format and symbols identical to Fig. 2.

five to eight times smaller than the linear summation and complete independence models' ratios.

In all of the summation-square plots, multidimensional thresholds were plotted against two probability summation contours representing psychometric function slopes of $k = 2$ and $k = 3$. These values were chosen as the psychometric function slopes obtained across all observers and conditions were close to these values. Fig. 5a shows the slopes of the psychometric functions obtained in all three experiments. The slopes were fit to the normalized data so that the magnitude of the slopes can be directly compared. Solid and open circles are the slopes for the unidimensional and multidimensional targets, respectively.

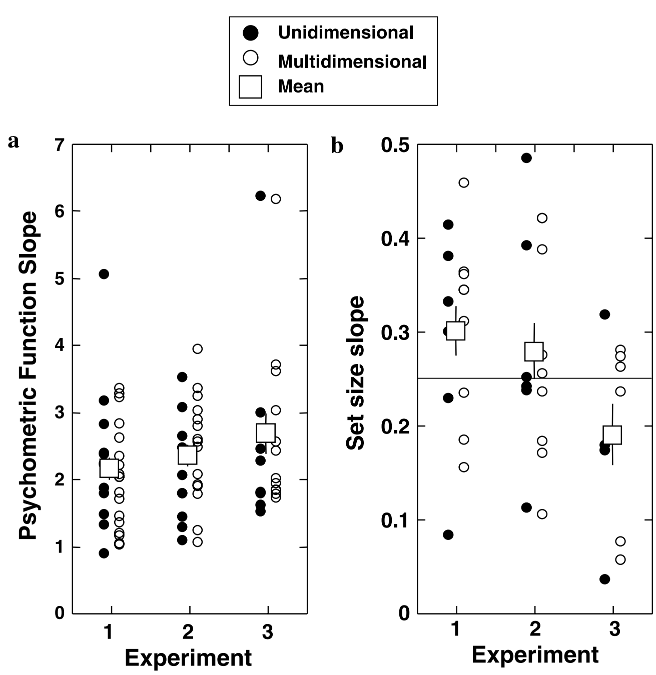


Fig. 5. (a) Psychometric function slopes for each condition (uni and multidimensional targets) and each experiment and (b) set size slopes estimated for each observer, each condition and each experiment. The means are shown as open squares and error bars are standard errors of the mean. The horizontal line in (b) shows a set size slope prediction (0.25) for a model assuming no capacity limit in attention.

Symbols have been offset for clarity. There were no clear differences between uni- and multidimensional targets. The open squares are the slope means for each experiment.

Lastly, set size slopes were calculated for each observer, each condition, and each experiment (Fig. 5b). Solid and open circles are the set size slopes for the unidimensional and multidimensional targets, respectively. Symbols have been offset for clarity. The open squares are the mean set size slope for each experiment. The measurements are quite variable but are generally consistent with a model assuming no capacity limit in attention (predicted slope of 0.25; see Palmer et al., 2000 for detail). Furthermore, there were no clear differences between uni- and multidimensional targets. This supports the assumptions that observers were able to monitor multiple feature mechanisms at multiple locations without a limit in attention capacity.

## 4. Discussion

Visual search is sometimes conceptualized as consisting of bottom–up and top–down components of information processing (e.g., Wolfe, 1994). Bottom–up refers to the flow of information from peripheral to more central stages of the visual system and top-down processes refers to information flowing from higher to lower visual areas. Top–down attentional processes have been shown to improve performance in various ways. For example, observers can ''ignore'' an entire set of distractors that were cued as irrelevant in color (Kaptein, Theeuwes, & van der Heijden, 1995). Pre-trial color cues can effectively reduce uncertainty associated with the presentation of multiple colored targets (Monnier & Nagy, 2001a, 2001b). Spatial cues indicating the location of a potential target have been shown to improve (e.g., Palmer et al., 1993), or even degrade (Carrasco & Yeshurun, 1998) search performance. In the present study, either a bottom–up or a top–down process could have been used to facilitate the search for multidimensional targets. Summation could have occurred as a bottom–up process with, for example, as a neural substrate, detectors simultaneously tuned to both dimensions. Linear summation could also have occurred via a top–down attentional process. Experimental conditions in the present experiments were constructed to maximize such top-down process by creating conditions with highly predictable stimuli as some have found that high levels of stimulus predictability tend to promote a performance advantage for multidimensional targets (Krummenacher, Müller, & Heller, 2001). Conditions were blocked by type (unidimensional vs. multidimensional) as well as search difficulty (the difference between the target and distractors was fixed within a block of trials). Despite such effort to reduce uncertainty, no evidence of summation beyond probability summation was obtained.

As in the present study, others have found performance advantages with multidimensional or redundantly coded targets (Krummenacher et al., 2001,2002; Shimozaki et al., 2002). The critical and difficult question is to precisely predict how much performance improvement to expect. Doing so using response time as a measure of performance is difficult because of the lack of quantitative models. The present study took advantage of well-established psychophysical principles (signal detection theory and rules of summation) to quantitatively assess summation for targets defined by multiple dimensions.

In a similar set of experiments, Shimozaki et al. (2002) and Shimozaki, Eckstein, and Abbey (2003) measured search performance for multidimensional targets. Their measurements showed a search performance advantage for multidimensional targets (targets that differed from the distractors in spatial frequency and orientation) but only when the target-to-distractor difference was small. With relatively large target-to-distractor differences, multidimensional targets did not result in better search performance compared to the unidimensional targets. A similar pattern of results was obtained using response time as a measure of performance (Monnier, 2002). In this reaction time study, one dimension (orientation) was fixed between the target and distractors while the other dimension (chromaticity) was systematically varied over a wide range. When the chromatic difference was small, RTs for the multidimensional targets were similar to the orientation only targets. When the chromatic difference was large, RTs for the multidimensional targets were similar to the color only targets. This indicates that when the chromatic difference is small, observers rely on the more salient orientation difference and switch to using chromaticity when the chromatic difference become more salient than the orientation difference. Only a small trend toward an advantage of multidimensional targets was observed, when both dimensions were approximately equally salient. The trend toward an advantage of multidimensional targets was speculated to be due to probability summation (Monnier, 2002) and was confirmed in the present study.

Shimozaki et al. (2002, 2003) have also show an advantage for multidimensional targets for small differences only, though their ideal observer analysis suggests multidimensional targets were detected by a neural substrate with simultaneous tuning to both dimensions. Furthermore, the ideal observer model also predicts the advantage of multidimensional targets should vanish at large target-to-distractor differences, as was observed. This prediction comes from the fact that the model is based on a cross-correlation of each element with ideal stimulus templates. As the target-to-distractor difference increases, the distractor template correlation decreases, predicting the advantage of multidimensional targets will vanish at large target-to-distractor differences. An alternative interpretation of their results is that for large differences, observers relied on the single, most discriminable dimension to detected the target (as suggested in Monnier, 2002).

One advantage of the present study is that the amount of expected probability summation was empirically estimated from the slope of the psychometric function. Furthermore, search performance was measured along normalized directions representing various ratios of two dimensions. This allowed for a rigorous assessment of the various summation models. Last, although the measurements were parsimoniously accounted for by a summation model supporting targets were detected by independent but noisy detectors, it is nonetheless possible that different stimulus conditions (conditions with a higher level of complexity) may reveal mechanisms that are tuned to multiple dimensions (e.g., Gegenfurtner et al., 1996; Leventhal et al., 1995). The measurements do indicate that, for the present conditions, targets were detected by noisy detectors independently tuned to the two dimensions.

## Acknowledgment

The stimuli were generated using C libraries developed by Linda Glennie and Steven K. Shevell at the University of Chicago (support under NIH EY-04802).

## References

Bauer, B., Jolicœur, P., & Cowan, W. B. (1998). The linear separability effect in colour visual search: ruling out the additive-colour hypothesis. *Perception & Psychophysics, 60*, 1083–1093.

Carrasco, M., & Yeshurun, Y. (1998). The contribution of covert attention to the set-size and eccentricity effects in visual search. *Journal of Experimental Psychology: Human Perception and Performance, 24*, 673–692.

Carter, E. C., & Carter, R. C. (1981). Color and conspicuousness. *Journal of the Optical Society of America A, 71*, 723–729.

Gegenfurtner, K. R., Kiper, D. C., & Fenstemaker, S. B. (1996). Processing of color, form, and motion in macaque are V2. *Visual Neuroscience, 13*, 161–172.

Graham, N. V. S. (1977). Visual detection of aperiodic spatial stimuli by probability summation among narrow band channels. *Vision Research, 17*, 637–652.

Graham, N. V. S. (1989). *Visual pattern analyzers*. New York: Oxford University Press.

Graham, N. V. S., & Nachmias, J. (1971). Detection of grating patterns containing two spatial frequencies: a comparison of single-channel and multiple-channels models. *Vision Research, 11*, 251–259.

Graham, N. V. S., Robson, J. G., & Nachmias, J. (1978). Grating summation in fovea and periphery. *Vision Research, 18*, 815–826.

Hubel, D. H., & Wiesel, T. N. (1968). Receptive fields and functional architecture of monkey striate cortex. *Journal of Physiology (London), 195*, 215–243.

Kaptein, N. A., Theeuwes, J., & van der Heijden, A. H. C. (1995). Search for a conjunctively defined target can be selectively limited to a color-defined subset of elements. *Journal of Experimental Psychology: Perception and Performance, 21*, 1053–1069.

Krummenacher, J., Müller, H. J., & Heller, D. (2001). Visual search for dimensionally redundant pop-out targets: evidence for parallel-coactive processing of dimensions. *Perception & Psychophysics, 63*, 901–917.

Krummenacher, J., Müller, H. J., & Heller, D. (2002). Visual search for dimensionally redundant pop-out targets: redundancy gains in compound tasks. *Visual Cognition, 9*, 801–837.

Leventhal, A. G., Thompson, K. G., Liu, D., Zhou, Y., & Ault, S. J. (1995). Concomitant sensitivity to orientation, direction, and color of cells in layers 2, 3, and 4 of monkey striate cortex. *The Journal of Neuroscience, 15*, 1808–1818.

Livingstone, M., & Hubel, D. H. (1988). Segregation of form, color, movement and depth: anatomy, physiology and perception. *Science, 240*, 740–749.

MacLeod, D. I. A., & Boynton, R. M. (1979). Chromaticity diagram showing cone excitation by stimuli of equal luminance. *Journal of the Optical Society of America, 69*, 1183–1185.

Monnier, P. (2002). Redundant coding assessed in a visual search task. *Displays, 24*, 49–55.

Monnier, P., & Nagy, A. L. (2001a). Uncertainty, attentional capacity, and chromatic mechanisms. *Vision Research, 41*, 313–328.

Monnier, P., & Nagy, A. L. (2001b). Set-size and chromatic uncertainty in an accuracy visual search task. *Vision Research, 41*, 3817–3827.

Mortensen, U. (2002). Additive noise, Weibull functions and the approximation of psychometric functions. *Vision Research, 42*, 2371–2393.

Nagy, A. L., & Sanchez, R. R. (1990). Critical color differences determined with a visual search task. *Journal of the Optical Society of America A, 7*, 1209–1217.

Palmer, J. (1994). Set-size effects in visual search: the effect of attention is independent of the stimulus tasks. *Vision Research, 34*, 1703–1721.

Palmer, J., Ames, C. T., & Lindsey, D. T. (1993). Measuring the effect of attention on simple visual search. *Journal of Experimental Psychology: Human Perception and Performance, 19*, 108–130.

Palmer, J., Verghese, P., & Pavel, M. (2000). The psychophysics of visual search. *Vision Research, 40*, 1227–1268.

Quick, R. F. (1974). A vector-magnitude model of contrast detection. *Kybernetik, 16*, 65–67.

Shimozaki, S. S., Eckstein, M. P., & Abbey, C. K. (2002). Stimulus information contaminates summation tests of independent neural representations of features. *Journal of Vision, 2*, 354–370.

Shimozaki, S. S., Eckstein, M. P., & Abbey, C. K. (2003). An ideal observer with channels versus feature-independent processing of spatial frequency and orientation in visual search performance. *Journal of the Optical Society of America A, 20*, 2197–2215.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*, 97–136.

Treisman, A., & Sato, S. (1990). Conjunction search revisited. *Journal of Experimental Psychology: Human Perception and Performance, 16*, 459–478.

Verghese, P. (2001). Visual search and attention: a signal detection theory approach. *Neuron, 31*, 523–535.

Wolfe, J. M. (1994). Guided search 2.0: a revised model of visual search. *Psychonomic Bulletin and Review, 1*, 202–238.

Wolfe, J. M. (2003). Moving towards solutions to some enduring controversies in visual search. *Trends in Cognitive Sciences, 7*(2), 70–76.