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The detection of feature singletons defined in two dimensions is based on salience summation, rather than on serial exhaustive or interactive race architectures

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Influential models of visual search assume that dimension-specific feature contrast signals are summed into a master saliency map in a coactive fashion. The main source of evidence for coactivation models, and against parallel race models, is violations of the race model inequality (RMI; Miller, 1982) by redundantly defined singleton feature targets. However, RMI violations do not rule out serial exhaustive (Townsend & Nozawa, 1997) or interactive race (Mordkoff & Yantis, 1991) architectures. These alternatives were tested in two experiments. In Experiment 1, we used a double-factorial design with singleton targets defined in two dimensions and at two levels of intensity, to distinguish between serial versus parallel models and self-terminating versus exhaustive stopping rules. In Experiment 2, we manipulated contingency benefits that are expected to affect the magnitude of redundancy gains and/or RMI violations on the assumption of an interactive race. The results of both experiments revealed redundancy gains as well as violations of the RMI, but the data pattern excluded serial-exhaustive and interactive race models as possible explanations for RMI violations. This result supports saliency summation (coactivation) models of search for singleton feature targets.

A common assumption made by most current models of visual search is saliency summation: Salience is computed in parallel in separate visual dimensions and is then summed onto a master salience map that guides the allocation of focal attention (see, e.g., Found & Müller, 1996; Gao, Mahadevan, & Vasconcelos, 2008; Itti & Koch, 2000; Koch & Ullman, 1985; Müller, Heller, & Ziegler, 1995; Wolfe, 1994; Wolfe, Cave, & Franzel, 1989). However, although it is by now a standard assumption, the empirical evidence for saliency summation is rather sparse (Krummenacher, Müller, & Heller, 2001, 2002; Nothdurft, 2000; Poirier, Gosselin, & Arguin, 2008), and there are alternative (serial, parallel-independent, or parallel-interactive) processing architectures with various stopping rules (self-terminating or exhaustive search). The aim of the present study was to strengthen the support for the assumption of saliency summation, vis-à-vis the alternative accounts.

Saliency Summation Models

In saliency summation models (see, e.g., Itti & Koch, 2000; Koch & Ullman, 1985; Treisman & Gelade, 1980; Wolfe, 1994), feature contrast is a measure of how different a specific location in the field is relative to its surrounding locations with regard to a particular feature. For example, with a red vertical bar surrounded by green vertical bars, feature contrast is high for "red" and low for "vertical." According to saliency summation models, feature contrast signals are pooled into dimension-specific maps (for an overview of dimensions in visual search, see Wolfe, 1998, and Wolfe & Horowitz, 2004) and are then summed into a supradimensional saliency or master map of the visual field. Activation at any location on the master map signals the presence of local feature differences, without providing information about the critical dimensions or features that give rise to these differences. The pattern of activations on

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the master map can be used to prioritize the deployment of focal attention for more detailed visual analysis.

The activity on the master map at a given location in 2-D space, $M(x, y)$, can be described as:

$$M(x, y) = \sum_{i \in I} D_i(x, y), \quad (1)$$

where I is a set of dimensions and $D_i(x, y)$ is the strength of feature contrast in dimension i at location (x, y).

Thus, the key features of salience summation models are (1) the determination of local feature contrast, (2) the summation of dimension-specific feature contrast signals into a master salience map, which (3) is topographically organized and (4) provides a featureless representation of local feature contrast(s), with (5) activation strength(s) indicating the strength(s) of local center-surround contrast(s).

There is neurophysiological evidence for key features (1) and (3) to (5). In early visual cortex, responses of single cells to their preferred stimuli are modulated by the presence of similar stimuli in the immediate vicinity, but outside of the cells' receptive fields (see, e.g., Kastner, Nothdurft, & Pigarev, 1997; Knierim & van Essen, 1992; Li, 1998, 2002). This modulation has been attributed to local inhibitory connections among cells with similar feature preferences (isofeature suppression). Among other structures, such as the pulvinar (see, e.g., Bundesen, Habekost, & Kyllingsbaek, 2005; Posner & Petersen, 1990) and the lateral intraparietal area (see, e.g., Colby & Goldberg, 1999; Gottlieb, 2002), the frontal eye fields (FEFs) are thought to be neuronal sites of a salience map (e.g., Bichot & Schall, 1999; Thompson & Bichot, 2005). Quite likely, rather than there being a single saliency map in the primate brain, saliency representations are implemented in a network of multiple interacting areas: the oculomotor network (Fecteau & Munoz, 2006). The FEF, for instance, is topographically organized so that neighboring neurons represent neighboring loci in retinotopic coordinates (Bruce, Goldberg, Bushnell, & Stanton, 1985, and Robinson & Fuchs, 1969, for monkeys; Kastner et al., 2007, for humans). Furthermore, the responses of FEF neurons have been characterized as being featureless, but feature contrast dependent by Sato, Murthy, Thompson, and Schall (2001): They observed the activity of visually responsive FEF cells to targets in their receptive fields to be the same, regardless of the specific dimension in which the target differed from distractors (motion or color). But greater similarity between targets and distractors affected the time course and the level of activity exhibited by FEF neurons: Target-specific activity (with a target in the cell's receptive field) separated later and to a lesser degree from distractor-specific activity (with a distractor in the receptive field).

However, to our knowledge, there is no direct neurophysiological evidence for the assumption that dimension-specific saliency signals are indeed summed into a master salience map.[1]

Behavioral Studies in Support of Salience Summation

There are few empirical studies that have attempted to examine the assumption that dimension-specific feature contrast signals are summed into a master salience map (Krummenacher et al., 2001, 2002; Nothdurft, 2000; Poirier et al., 2008; Turatto, Mazza, Savazzi, & Marzi, 2004). These studies relied either on measuring salience as reported by the observers (indirectly in Poirier et al., 2008; directly in Nothdurft, 2000) or on an analysis of reaction time (RT) distributions in a redundant-signals paradigm (Krummenacher et al., 2001, 2002; Turatto et al., 2004). Concerning saliency judgments, both Nothdurft and Poirier et al. suggested that feature contrast signals from different dimensions are combined in a master salience map, although not in a simple additive, but rather in a slightly subadditive, fashion. However, it remains unclear whether rated saliency reflects the preattentive processes that mediate the allocation of focal attention in real time. And, although the studies that used the redundant-signals paradigm are nearer to these processes, they leave room for alternative interpretations (see below).

Given this background, the present study was designed to reexamine the assumption of salience summation using the redundant-signals paradigm in visual search for feature singletons (as in Krummenacher et al., 2001, 2002), while including additional manipulations that permitted alternative processing architectures to be tested.

Parallel-Independent and Coactivation Models

In general, in the redundant-signals paradigm, the observer's task is to respond as quickly as possible to the onset of a stimulus that belongs to a predefined set of target stimuli (choice RT task), with each of the possible targets being mapped to the same response. Performance on trials on which redundant signals are presented is then compared with that on trials with only a single signal. The redundant-signals effect (RSE) is the RT advantage for redundant- relative to single-signal trials. This paradigm has been used widely (see, e.g., Corballis, 2002; Giray & Ulrich, 1993; Katzner, Busse, & Treue, 2006; Krummenacher et al., 2001, 2002; Marzi et al., 1996; Miller, 1982, 1986; Mordkoff & Yantis, 1991, 1993; Turatto et al., 2004) to address a multitude of issues ranging from multimodal (e.g., visual and auditory) processing to selection from two locations and the discrimination of dual features (divided attention). To illustrate the relevance of the redundant-signals paradigm to the question at issue in the present study, it is useful to review the various processing architectures that have been proposed to explain the RSE in the redundant-signals paradigm.

Regardless of the specific questions examined and the nature of the signals used, the RSE can be explained in several mutually exclusive ways. Raab (1962) accounted for the RSE in terms of statistical facilitation. He proposed that redundant targets are processed in a multichannel system that can be likened to a "horse race": The target signal that is processed the fastest triggers the response (i.e., "wins the race") and determines the RT (Figure 1A; see also Schönwälder, 2006; Townsend & Nozawa, 1995; Zehetleitner, Müller, & Krummenacher, 2008). Thus, on each redundant-signal trial, the two single signals are processed in parallel by independent processors, and they accumulate evidence that triggers the response when a

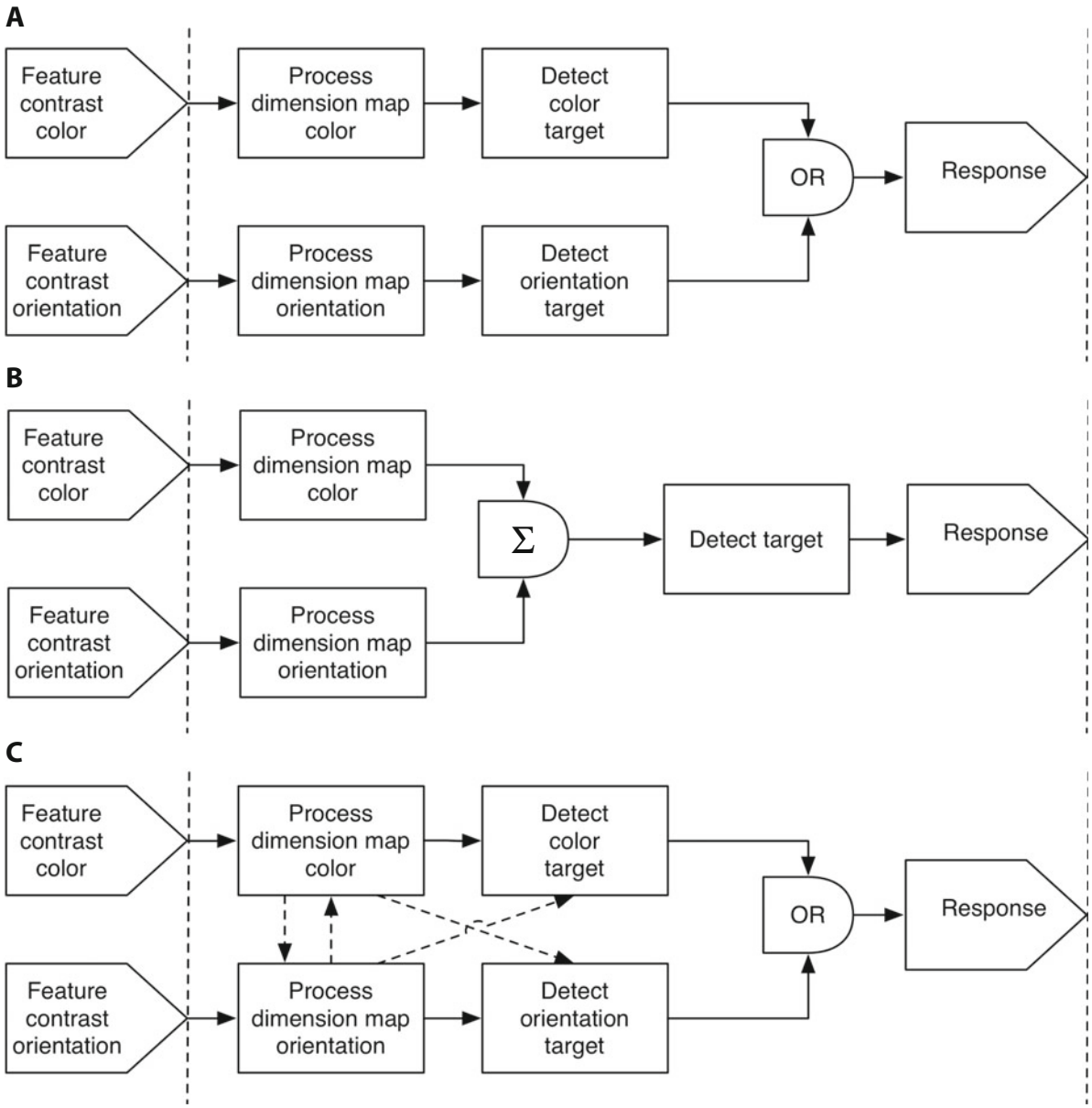

Figure 1. (A) In an independent parallel race model, two simultaneously presented stimuli are processed in parallel until one or both triggers a target-present response. In the context of visual pop-out search, the stimuli in the two processing channels are simultaneous feature contrast signals in separate dimensions (e.g., luminance and orientation). (B) In a parallel coactivation model, the signals from both channels are integrated/pooled. This summed signal triggers a target-present response. (C) The interactive race model is similar to the parallel race model, with the addition that the two processing channels can exchange information, for example, about the presence or absence of a signal in the respective other channel. The two possible routes for exchanging information are indicated by dashed arrows. Panel C is from "An Interactive Race Model of Divided Attention," by J. T. Mordkoff and S. Yantis, 1991, *Journal of Experimental Psychology: Human Perception and Performance*, *17*, p. 522. Copyright 1991 by the American Psychological Association. Adapted with permission.

threshold is exceeded. If the distributions of the RTs to the two single signals overlap and two processing times are drawn on redundant-signal trials (one for each of the two single signals), then—mimicking the parallel race model—the faster of the two (drawn) times is taken as the redundant-signal RT. This results in a mean RT gain (the RSE), because processing is terminated as soon as the response threshold is exceeded in one of the channels.

As an example, Figure 2 presents simulated density functions from normally distributed single-signal RTs: S1 and S2, with means of 350 and 355 msec (dashed and dotted lines), respectively. The solid line represents the density function generated by a simulated race model: For each trial, one RT was drawn from the S1 distribution, and one from the S2 distribution. The faster of both RTs was taken as the "race winner." As can be seen, the (simu-

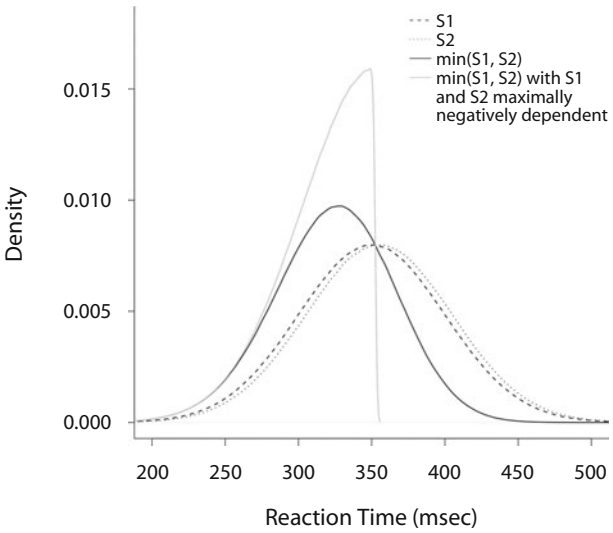

Figure 2. The density functions of two single signals—for example, orientation (black dashed line) and luminance (black dotted line). The black solid line represents the distribution of a parallel race between both single signals—that is, as generated by a race model. The gray line depicts the minimum of both single target distributions, with the assumption of maximal negative dependency between the single signals. This, according to the race model inequality, is the largest benefit that redundant-signals trials can have under the assumption of a race model.

lated) distribution of the redundant-target RTs simulated is shifted to the left on the time axis; that is, there is a redundancy gain of 25 msec. In summary, Raab (1962) explained the RSE by assuming an independent parallel race between the two target-defining signals on redundant-target trials, resulting in an RT distribution that is shifted to the left of the distributions for the two single signals.

Miller (1982) demonstrated that explanations that are based on statistical facilitation in a parallel race model yield a bound to the RSE, which is inherent in the race model. The solid line in Figure 2 represents a race model with statistically independent signals S1 and S2. However, if S1 and S2 are negatively dependent—that is, each time, a fast RT is drawn from the S1 distribution a slow one from the S2 distribution, and vice versa—the gain from taking the winner of the race is maximal. The gray line in Figure 2 represents the density function generated by a race model simulation in which S1 and S2 were maximally negatively dependent, which yielded an even larger redundancy gain of about 40 msec. If the RT redundancy gain exceeds this boundary defined in the race model inequality (RMI; see below), statistical facilitation within a parallel race architecture can no longer account for the RSE. As an alternative, Miller (1982) proposed a coactivation architecture in which the single signals on a redundant-signal trial are integrated prior to response generation (see Figure 1B). That is, on a redundant-signal trial, the activations generated by both single signals (in separate processing channels) are pooled, and can thus trigger the response faster than single-signal trials. This is because there are two sources of activation on redundant-signal trials, as compared with just one on single-signal trials. In brief, Miller (1982) proposed a taxonomy of cognitive processes on the basis of the distinction between separate versus integrated processing architectures.

The Redundant-Signals Paradigm in Visual Search for Singleton Feature Targets

In summary, both parallel race and coactivation models assume two parallel channels or processors, but differ in their assumptions of how these processors contribute to making a detection decision. In bimodal versions of the redundant-signals paradigm, stimuli may be, say, either auditory or visual (i.e., singly defined, originating from one of two possible modalities), or both auditory and visual (redundantly defined, originating from both dimensions). In this case, the two channels correspond to modality-specific processing structures in the brain. Similarly, in divided-attention versions of the redundant-signals paradigm, a dot of light may be presented at either one or the other of two possible locations, or one dot at both locations. In this case, the two channels correspond to location-specific processing structures in the visual system.

But how might we conceive of the two channels in visual search for salient feature singletons, where the target differs from multiple distractors in either one or the other of two possible dimensions (e.g., in either color or orientation), or in both dimensions (in both color and orientation) (see, e.g., Krummenacher et al., 2001, 2002)? To start with, Krummenacher et al. (2001, 2002) assumed that simple (target presence) detection decisions are based on the same (master map salience) signal that mediates focal-attentional selection; that is, rather than detection responses requiring focal-attentional selection and explicit target analysis (as assumed by, e.g., J. Johnston & Pashler, 1990), the same signal that triggers an attentional "orienting response" (e.g., Posner, 1980) to the target may also permit the initiation of a manual detection response, while further focal-attentional processing of the target is still going on. Consistent with this assumption, Müller, Krummenacher, and Heller (2004) found that simple detection decisions may be made without explicit encoding, or knowledge, of the target-defining dimension or feature. This would be an instance of what Neumann (e.g., 1989; Neumann & Klotz, 1994) has referred to as "direct parameter specification," which permits for instructed responses to be triggered by information of which the observers remain unaware.[2] In any case, whether detection responses are direct or mediated by focal attention, search performance is dependent on the time required by the salience map to generate an attention-summoning signal.

Furthermore, in the redundant-signals detection paradigm, with the target differing from the distractors in either one or the other of two dimensions or in both dimensions, the two channels correspond to dimension-specific visual processing pathways—for which there is ample neurophysiological (see, e.g., Hubel & Livingstone, 1987; Livingstone & Hubel, 1988) as well as behavioral (e.g., Treisman, 1988) evidence, and which are a standard as-

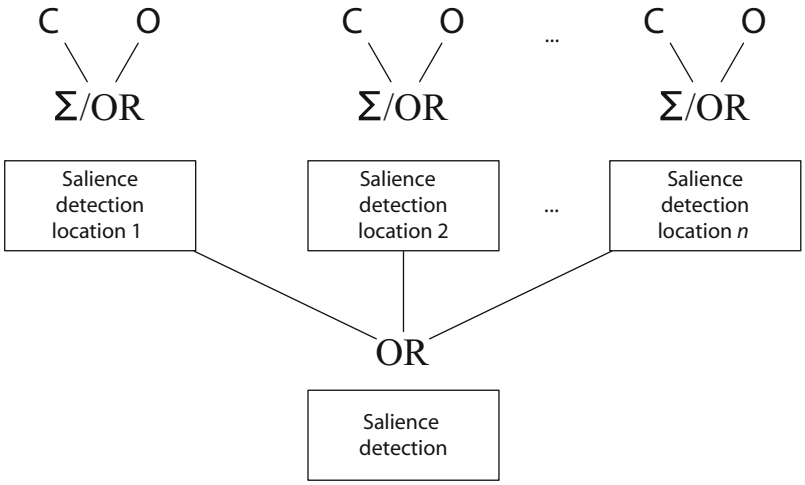

Figure 3. At each location at which an item is present in the display, the presence of a strong salience signal is detected dependent on color- (C) and/or orientation- (O) specific feature contrast signals, which can be either integrated (sum sign) or processed in parallel (OR). For focal-attentional selection, the location is selected that first generates a strong salience signal. For detection, a detection response can be triggered based on a parallel (OR) race of the salience processing units at each location; that is, a detection response is initiated as soon as any of the processing units has detected a salience signal.

sumption in current theories of visual search (e.g., Itti & Koch, 2000; Treisman & Gelade, 1980; Wolfe, 1994).

Given this dimensional segregation of visual pathways, one possible architecture that permits the application of the RMI to situations with more than two items being present on any given trial is depicted in Figure 3. The general idea is that for set size *n*, a detection decision is made for each item in the display. Each detection decision is processed according to either a parallel OR or a coactive summation rule given the feature contrast calculated in the two dimensional channels (in the example, color and orientation). A target-present response is triggered as soon as one of the *n* (master map) detection units signals the presence of a target (a selection—or "attentional orienting"—response could be triggered in the same way: That item is selected for which a detection unit signals the presence of a target first). Furthermore, the time until response can be considered to be a random variable, which is the minimum of the detection times for each of the *n* detection units. On the assumptions that (1) the time until activity on the master map at a target location exceeds a certain threshold, and (2) the threshold is never reached at nontarget locations, a parallel race model would predict the observed RT to be the minimum of the detection times for each of the two dimensions (i.e., the RMI holds; for details, refer to Appendix A). Summation models, by contrast, predict violations of the RMI. Thus, because each detection unit could, in principle, process dimension-specific feature contrast signals according to either a parallel or a summation rule, for calculation of the RMI, the situation of *n* items being coupled with an OR rule collapses to a two-channel architecture.

However, there are several alternative models of singleton detection. One, for example, is envisaged in feature integration theory (FIT; Treisman & Gormican, 1988). According to FIT, detection responses may be based directly on the activity in "dimensional modules" (which may be thought of as summing feature contrast signals within a given dimension; see Krummenacher et al., 2002); that is, a detection response is triggered as soon as the activity of such a module exceeds threshold. Note that Treisman's (1988) original assumption was that dimensional modules have to be checked for the presence of an above-threshold signal in a serial fashion (a possibility that will be of relevance in the section below; see Chan & Hayward, 2009, for a revival of this proposal). However, it is also conceivable that dimensional modules are processed in parallel; that is, a detection response may be triggered as soon as activity in one of the dimensional modules reaches threshold, which reduces to a classical race model (see Figure 1A).

Fundamentally, however, although it is uncontested that violations of the RMI are sufficient to rule out parallel race models of search for redundantly defined singleton feature targets, whether the violations can be taken as (sufficient) evidence for coactive processing of dimension-specific signals is open to question. In particular, there are two lines of argument that consider violations of the RMI to be a necessary, but not sufficient, condition for coactive processing.

Violations of the RMI by Models That Do Not Assume Coactivation

Townsend and Nozawa (1997) have shown that there exists another class of models that may give rise to violations of the RMI—namely, models assuming serial processing combined with an exhaustive stopping rule (i.e., search is terminated only once all items have been processed, even

if the target is detected before the last item). With regard to singleton feature search (see above), an example of such a serial-exhaustive-search model would be to check both channels of dimensional feature contrast on each trial, one after the other (e.g., "is there a color target?" followed by "is there an orientation target?")—a strategy that observers might adopt to avoid target miss errors. Such a double-check strategy would result in increased RTs on single-target trials, provided that it takes longer, statistically, to determine the absence of a signal in a channel as compared with its presence, which is the norm in the relevant pop-out search studies (e.g., Found & Müller, 1996; Treisman & Gormican, 1988; see also Chun & Wolfe, 1996). Indeed, FIT (Treisman & Gelade, 1980; Treisman & Gormican, 1988; see also Chan & Hayward, 2009) assumes detection of singletons to involve a serial process of checking for activity in dimensional modules. Consequently, serial exhaustive search of dimensional modules has to be considered as an alternative to saliency summation models. In the light of this alternative architecture, the present study was aimed at testing saliency summation models (e.g., guided search) versus serial models (e.g., FIT) of singleton feature search.

Another issue to be taken into account by interpretations assuming coactivation is that, contrary to the aforementioned theoretical accounts of pop-out search, dimension-based signal processing may not completely separate at early stages. Thus, Mordkoff and Yantis (1991) proposed a variant of a parallel race model in which dimension-based channels may exchange information before a response is selected—the interactive race model (see Figure 1C). Mordkoff and Yantis (1991) showed that the existence of contingencies between the channels of a parallel race (e.g., several dimensional maps), which favor redundant relative to single targets, may give rise to violations of the RMI that are not caused by coactive processing of the single signals. Consistent with the interactive race model, using a divided-attention paradigm, Mordkoff and Yantis (1991) found that violations of the RMI disappeared after contingencies that potentially favored redundant over single targets were removed.

Thus, given these model alternatives, relying on the redundant-signals paradigm combined with tests for violations of the RMI as the sole tool of analysis is inconclusive: Although violations of the RMI do rule out independent parallel models, both serial exhaustive and interactive race models may provide feasible alternatives to coactivation models.

However, based on measures derived from systems-factorial methodology (Sternberg, 1969; Townsend & Ashby, 1983), Townsend and Nozawa (1995) devised a procedure that permits different types of processing architectures and stopping rules to be distinguished. Adopting this procedure, combining a double-factorial design with the redundant-signals paradigm, a thorough analysis of the cognitive mechanisms underlying visual search for redundantly defined pop-out targets becomes possible, especially with regard to the stopping rule (exhaustive or self-terminating) and architecture (serial, parallel, or coactive). Moreover, if pop-out search displays are processed in terms of an interactive race model, manipulations of contingencies that favor redundant over single targets should affect the magnitude of RT redundancy gains and violations of the RMI.

In summary, models of singleton feature detection can be categorized along two dimensions: architecture and the stopping rule. In terms of architecture, feature contrast from two dimensions can be processed in parallel or serially. Parallel processing can be independent, interactive, or coactive. Models of independent parallel processing assume that a detection response is triggered as soon as dimension-specific feature contrast computations provide enough evidence for the presence of a feature singleton in one dimension—with the additional assumption that the processing of feature contrast in one dimension does not affect the processing in any other dimension (Figure 1A). The latter assumption is abandoned by interactive race models that allow for interactions between dimensions; that is, either calculation of feature contrast in one dimension is affected by processing of feature contrast in a different dimension, or the process of detection in one dimension is affected by the result of detection in a different dimension (Figure 1C). In contrast, in coactive parallel models, feature contrast is calculated independently and in parallel for both dimensions, and target detection depends on the integration of feature contrast from both dimensions (Figure 1B).

The stopping rule in serial and parallel (independent or interactive) models can be either self-terminating (i.e., search is terminated as soon as one channel signals target presence) or exhaustive (i.e., both dimensions are checked, even if a target has already been detected in one dimension). Of relevance for the present study are parallel coactivation, serial exhaustive search, and interactive race models, because these three are known to lead to violations of the RMI in redundant-signals paradigms (Miller, 1982; Mordkoff & Yantis, 1991; Townsend & Nozawa, 1997). The aim of the present study was to verify that RMI violations in redundant pop-out target search (Krummenacher et al., 2001, 2002) are indeed indicative of coactive processing as assumed by saliency summation models, and that the alternative processing architectures of serial-exhaustive and parallel-interactive processing do not hold.

Overview of the Present Study

To this end, two experiments were carried out, the first using a double-factorial redundant-target paradigm, and the second manipulating the contingencies favoring redundant over single targets. In both experiments, observers performed a visual search (detection task) for a singleton pop-out target that differed from the distractor items in either one dimension (orientation only or luminance only) or both dimensions. Observers were to respond "target-present" to the presence of any odd-one-out item in the display, whether defined by luminance only, orientation only, or both luminance and orientation. The aim of Experiment 1 was to investigate which of the aforementioned model alternatives (coactive, serial exhaustive, or interactive race) is capable of explaining performance

in terms of architecture (serial, parallel) and stopping rule (exhaustive, self-terminating). For each signal channel, the two factors of the double-factorial design were the absence versus presence of a target and the intensity (in terms of strength of feature contrast) of the target relative to the distractors (orientation contrast, 6º vs. 45º orientation difference between targets and distractors; luminance contrast, adjusted on an individual basis to match the RTs for the two orientation targets). In Experiment 2, the ratios of target-present to target-absent trials (1:1 vs. 3:1) and of single to redundant targets (2:1 vs. 1:1 for single:redundant targets) were manipulated, varying the target response and interstimulus contingencies between conditions. Dependent on these contingencies, interactive race models make predictions about the size of redundancy gains and the magnitude of RMI violations. On the basis of saliency summation models, we hypothesized that the RSE in search for pop-out targets would be accounted for only by coactivation models, and that neither the predictions of serial exhaustive nor those of interactive race models would be satisfied.

EXPERIMENT 1

In Experiment 1, we employed a double-factorial design combined with a redundant-target paradigm, as was proposed by Townsend and Nozawa (1995). In contrast with previous studies that employed this method (Nozawa, Reuter-Lorenz, & Hughes, 1994; Patching & Quinlan, 2004; Townsend & Nozawa, 1995), in the present experiments, we investigated how dimensional feature contrast signals are processed in visual search for feature singletons, according to saliency summation (e.g., Wolfe, 1994) or alternative models (e.g., serial checking, Chan & Hayward, 2009; Treisman & Gelade, 1980). Second, instead of requiring observers to make a simple manual response to the onset of one stimulus presented at a fixed location (Patching & Quinlan, 2004; Townsend & Nozawa, 1995) or saccade to a target stimulus presented at one of two possible locations (Nozawa et al., 1994), in the present study, the redundant-signals paradigm was implemented in a visual-search task in which a detection response had to be given if one (target) item differed from the surrounding (distractor) items in one or two dimensions (similar to Krummenacher et al., 2001, 2002, and Turatto et al., 2004).

Accordingly, the manipulation of signal intensity (which is required in the Townsend–Nozawa, 1995, double-factorial design) in the present study also differed from that in previous studies (in which intensity was manipulated by varying the brightness of a target dot or the loudness of a target tone). Specifically, in the present Experiment 1, the intensity of dimensional feature contrast signals was varied by manipulating target–distractor similarity, on the basis of the observation that the processing of saliency is slower the higher the target–distractor similarity (e.g., Sato et al., 2001). Thus, varying target–distractor similarity permitted the processing times in the two dimensional channels to be manipulated independently in Experiment 1 (see Figure 1).

In more detail, the double-factorial design is derived from Sternberg's (1969) additive-factors method. Applied to the pop-out search paradigm, it combines the presentation of a singleton feature target defined in one or both of the two possible dimensions with the factorial manipulation of a second variable—here, the strength of feature contrast. Townsend and Nozawa (1995) demonstrated that by analyzing the interaction between feature contrasts in both dimensions of redundant targets, the types of architecture and stopping rule can be differentiated. There are four possible redundant targets in the redundant-dimensions visual-search paradigm: two dimensions × two levels of feature contrast. In the present study, with orientation and luminance as the critical dimensions, orientation targets could differ from distractors by an orientation difference of 6º (low feature contrast) or 45º (high contrast), whereas luminance targets could be either dim (low feature contrast) or bright (high contrast; see the Method section for details). Thus, the four different types of redundant targets were (1) tilted by 45º relative to the vertical and bright, (2) tilted 45º and dim, (3) tilted 6º and bright, and (4) tilted 6º and dim.

For redundant-signals trials, the intensity variation allows for analyses and a model test based on systems-factorial methodology: the "mean interaction contrast" (Townsend & Nozawa, 1995). The mean interaction contrast quantifies the interaction between two factors and is 0 for no interaction, negative for a subadditive effect, and positive for a superadditive effect. In the present context, the interaction of interest refers to the two simultaneously presented signal components of redundant targets. By manipulating the intensity of each component signal, it becomes possible to examine the interaction of the intensity manipulation of Component 1 with the intensity manipulation of Component 2. Townsend and Nozawa (1995) proved that parallel (race as well as coactivation) models predict superadditivity in the mean interaction contrast, that parallel exhaustive models predict subadditivity, and that both exhaustive and self-terminating serial models predict simple additivity. Experiment 1 was designed to distinguish between serial exhaustive and coactivation models as potential alternative explanations of the RSE. On the basis of the saliency summation models (such as guided search of Wolfe et al., 1989, and Wolfe, 1994; or the dimension-weighting account of Müller et al., 1995; Müller et al., 2004), it was expected that serial-exhaustive models as well as parallel race models can be ruled out, and that coactivation models can exclusively account for the RSE.

In more detail, the prediction was that if the two factors—signal intensity in Channel 1 (orientation) and signal intensity in Channel 2 (luminance)—are independent, they should have an additive (noninteracting) effect on the processing speed for redundant targets. That is, the slowing of RTs because of low feature contrast in one dimension should not be affected by the feature contrast in the other dimension. This additivity would provide evidence for serial models. Subadditivity occurs if lowering the feature contrast in one dimension has a smaller slowing effect on RTs when the feature contrast in the other

dimension is already low (which would provide evidence for parallel exhaustive models). If reducing the feature difference in one dimension has a larger effect when the feature in the second dimension is of a low (rather than of a high) contrast, superadditivity is expected to occur (arguing in favor of parallel race or coactivation models). Saliency summation models predict violations of the RMI and a superadditive interaction contrast—that is, evidence for a summation of dimensional signals as the cause of the RT benefits for redundantly, relative to singly, defined targets in pop-out search.

Method

Participants. Fourteen observers took part in Experiment 1 (4 male; 1 left-handed; age range, 19–46 years; median age, 24.0 years). They were paid at a rate of €8 (~$12) per hour.

Apparatus. The stimuli were presented on a Sony Multiscan E250 17-in. monitor (screen refresh rate 85 Hz, screen resolution 1,024 × 768 pixels), driven by a personal computer running under the Windows XP operating system, which also controlled the recording of RTs. The apparatus was placed in a sound-isolated room with black walls, with a dim light behind the monitor to prevent reflections on the screen. The viewing distance was about 62 cm and was maintained by a chinrest. Observers performed a go/no-go task: They responded by pressing the right button of the computer mouse with their right-hand index finger when a target was present, and they withheld a response when no target was present. At the end of each trial block, observers were informed about their mean RT and error rate in the block.

Stimuli and Timing. The display consisted of a 6 × 6 array of filled upright bars that were 2.55º of visual angle in height × 0.65º in width, on a black background (0.2 cd/m^2). The vertical and horizontal (center to center) distances between adjacent bars were 4.35º, with a jitter of 0.2º. The bars were either dark gray, 7.5 cd/m^2 (distractors), or light gray (targets), with the luminance of the target bars set individually for each observer (see below). There were four single- and four redundant-target conditions. Orientation targets differed from the vertical distractors by a rotation to the left or the right of either 6º (low contrast) or 45º (high contrast). Luminance targets were brighter than dark gray distractors, and their intensity levels were determined for each observer prior to the main experiment by adjusting them so as to yield detection RTs comparable to those for the high- and low-contrast orientation targets, respectively (on average, 69.8 cd/m^2 for high-contrast and 20 cd/m^2 for low-contrast luminance targets). Redundant targets were defined by a combination of orientation contrast (6º, 45º) × luminance contrast (20 cd/m^2, 69.8 cd/m^2) relative to the vertical, dark gray distractors. Targets were always presented at one of the central 4 × 4 matrix locations, so that they were completely surrounded by (eight) distractor items; observers were not informed about this restriction. A target was present in 60% of all trials, in all trial blocks.

Trials started with the simultaneous onset of all display items, which remained visible until the observer produced a response, but no longer than 1,000 msec. After an intertrial interval of 1,000 msec plus a temporal jitter of up to 200 msec, the next trial started. Observers were instructed to press the right mouse button on target-present trials (go condition), and to refrain from responding on target-absent trials (no-go condition). Following an erroneous response or failure to respond, the interstimulus interval was increased to 2 sec. In the practice and adaptation phases of the experiment, on target-present trials, an equal number of orientation and luminance targets were presented. In the main experiment, the target dimension was determined randomly for each single-signal trial. The ratio of single- to redundant-signal trials was 2:1.

Design and Procedure. Experiment 1 consisted of two 1-h sessions on consecutive days. Both started with a practice block of 30 trials (data not included in the analysis). In Session 1, in the first 6 blocks following practice, the saliency (brightness) of the luminance targets was adapted to that of the orientation targets for the two intensities (low, high) so that the median RTs were statistically equal for the two types of a target. In Adaptation Blocks 1–3, only trials with orientation targets were presented (besides target-absent trials), so as to estimate the median RTs to orientation targets. Then, in Blocks 4–6, the brightness of the luminance targets was adjusted using an adaptive-staircase procedure (following that of E. B. Johnston, Cumming, & Parker, 1993): On each target-present trial, the RT to the luminance target was compared with the median RT for the orientation targets; if the luminance RT was faster than the orientation median RT, the luminance of the next target was decreased, and if it was slower, luminance was increased. Luminance was controlled using 6-bit RGB values (ranging from 0 to 65), and step size decreased from 8 to 1 with each reversal of the staircase. The brightness values thus established were then introduced in the main experiment. Following the adaptation phase, observers performed 16 trial blocks in Session 1, and 20 blocks in Session 2, all with 60 trials per block—yielding a total of 2,160 trials (exclusive of practice and adaptation trials).

Data analysis. For all RT analyses, target-absent and error trials were excluded. The remaining data were analyzed in three steps: (1) mean RTs, (2) RT distribution measures, and (3) statistical testing of distribution measures to examine for violations of the RMI.

Mean RT analysis. The mean RTs were subjected to a repeated measures ANOVA with the factors of target dimension (orientation, luminance) and intensity (low, high). Additionally (for Experiment 1 only), the mean interaction contrast (IC) was calculated for redundant-signal trials according to the following equation:

$$\mathrm{IC} = \mathrm{RT}(l, l) - \mathrm{RT}(l, h) - \mathrm{RT}(h, l) + \mathrm{RT}(h, h), \qquad (2)$$

where l denotes low intensities (i.e., dim luminance or 6º orientation contrast) and h denotes high intensities (i.e., bright luminance or large 45º orientation contrast) of the target relative to distractor items [e.g., RT(h, l) denotes the mean RT to redundant targets differing from distractors by a high orientation contrast and a low luminance contrast, with the intensity of orientation contrast specified first and that of luminance contrast second].

The RSE is the RT benefit for redundant targets relative to the corresponding single targets (e.g., high- and, respectively, low-contrast orientation and luminance single targets for a redundant target of a 45º orientation and low luminance contrast). To avoid overestimating the redundancy gains, we used a procedure proposed by Miller and Lopes (1988; see also Krummenacher et al., 2001, 2002). This involves determining, for each observer, whether one of the single targets is favored, using a two-sided t test with a criterion of $\alpha = .1$. If no single target dimension is favored, the mean RTs are averaged across both single-target dimensions; if one of the single-target dimensions is favored, the mean RT for the favored dimension is compared with that for redundant-signal trials. Applied to the data of Experiment 1, for each observer, the mean RT for the faster single signal was compared with the mean RT for redundant targets.

The RMI. Miller (1982) formalized the RMI as follows:

$$P(\mathrm{RT} < t \mid S_{12}) \leq P(\mathrm{RT} < t \mid S_1) + P(\mathrm{RT} < t \mid S_2), \qquad (3)$$

where S_i denotes a single signal presented in channel i, and S_{ij} a redundant signal presented in channels i and j. The inequality states that the probability that the RT on a redundant-signal trial is faster than a given time t is always less than or equal to the sum of the corresponding probabilities on single-signal trials, thus providing a bound of how large the RT benefit on redundant- relative to single-signal trials may be under the assumption of a race model. Testing the predictions of the RMI usually involves the determination of the cumulative density functions (CDFs) of RTs obtained on redundant- and single-signal trials (separately for each type of single signal). The sum of the two single-signal trial CDFs is then related to the CDF for redundant-signal trials. If the difference between the cumulative probabilities is smaller than 0, any observed RSE is in accordance with the race model assumption. To deal with the

somewhat unintuitive property of the sum of two single-signal CDFs converging to 2 (rather than 1, as in density functions), we adopted an alternative formulation of the RMI proposed by Colonius and Diederich (2006). They demonstrated that the minimum of the sum of the two CDFs and 1, $\min[1, P(\mathrm{RT} < t \mid S_1) + P(\mathrm{RT} < t \mid S_2)]$, is also a CDF. If the CDFs are given by $P(\mathrm{RT} < t \mid S_1) = G_1(t)$, $P(\mathrm{RT} < t \mid S_2) = G_2(t)$, and $P(\mathrm{RT} < t \mid S_{12}) = F(t)$, the null hypothesis of the parallel race model is

$$H_0 : d(t) = F(t) - \min[1, G_1(t) + G_2(t)] \leq 0, \tag{4}$$

where $d(t)$ denotes the Kolmogorov distance between the two distributions $F(t)$ (i.e., the distribution based on the redundant-signals RTs) and $\min[1, G_1(t) + G_2(t)]$ (i.e., the distribution corresponding to the maximum possible benefit for redundant signals as compared with that for single signals under the race model assumption). The race model predicts the distance $d(t)$ to be smaller than 0. This formulation also permits the magnitude of violations of the RMI to be quantified, in terms of the area under $d(t)$ (Colonius & Diederich, 2006), which is important for examining whether there are larger or smaller RMI violations dependent on experimental conditions.

To test whether $d(t)$ differs significantly from 0 for a particular point in time t, we employed the method of vincentization (see, e.g., Kiesel, Miller, & Ulrich, 2007; Miller, 1982). Accordingly, the group distribution is calculated by evaluating $d(t)$ for each observer at a defined number of quantiles. The statistical significance of potential violations is examined using t tests for each quantile qi. Methodologically, however, one drawback of this procedure is that the group distribution values of $d(t)$ for successive quantiles of the vincentized distribution are not independent. This may result in an overestimation of RMI violations, because, if the RMI is violated at a particular quantile, violations at neighboring points are likely to occur as well (Kiesel et al., 2007; Van Zandt, 2002). Artificial overestimations of RMI violations can be reduced if a large number (>20) of observations is used to estimate the CDF, and if the inequality is tested within a limited range of quantiles—for example, between .05 and .20 only (Kiesel et al., 2007). In the present Experiment 1, the number of observations per condition ranged from 94 to 205, with a median of 141.1, and the range of quantiles at which the RMI was tested was restricted to four (.05 to .2).

Furthermore, anticipations were removed from the distribution of target-present RTs using the "kill-the-twin" procedure introduced by Eriksen (1988): For each false alarm response, a correct target-present response with an RT within ±2 msec of the false alarm RT was removed from the analysis (also see Krummenacher et al., 2001, 2002).

Results

Trials with RTs shorter than 200 msec, which were categorized as anticipations (<0.1% of all trials), and trials with response errors (0.8% misses and 2.4% false alarms) were excluded from further analysis. The RTs for single- and redundant-signal trials are depicted in Figure 4.

First, we examined only single-signal data, in order to test whether the manipulation of feature contrast (which was necessary for the double-factorial design) was successful (see Figure 4 for the RTs on single- and redundant-target trials). A 2 × 2 repeated measures ANOVA with the factors dimension (orientation, luminance) and feature contrast (low, high) revealed a significant main effect of feature contrast [$F(1,13) = 82.5$, $p < .001$]. Low-contrast targets were processed considerably slower than were high-contrast targets: 477 versus 372 msec. The RT difference between orientation- and luminance-defined targets (417.5 vs. 431.2 msec) was not significant [$F(1,13) = 2.4$, $p < .15$], nor was the interaction of dimension with feature contrast [$F(1,13) < 1$; n.s.]. In order to test whether low-feature contrast targets did still "pop out," we performed a display size experiment (with different observers; see Appendix B), which revealed low-contrast targets to be detected efficiently (the slope of the function relating detection RT to display size was less than 5 msec/item). Although there is no definite slope criterion that distinguishes efficient from inefficient search, 80% of all feature searches have a slope that is less than 5 msec/item (Wolfe, 1998; e.g., 3 msec/item for the feature searches of Treisman & Gelade, 1980), and the slopes produced by our low-feature contrast targets

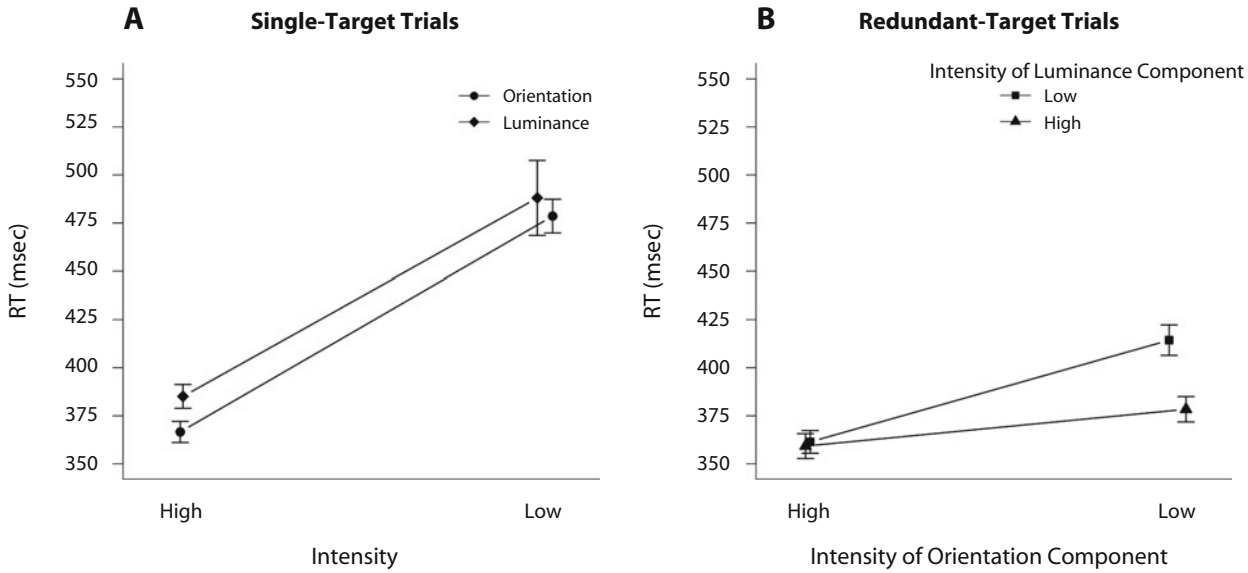

Figure 4. Mean reaction times (RTs) for the single-signal (A) and redundant-signal (B) trials for the different conditions of intensity with standard errors of the means.

were equal to or less than 5 msec/item (see Appendix B). Thus, targets of both high- and low-feature contrast are processed in the same (spatially) parallel fashion, and the intensity manipulation necessary for the double-factorial design was successful.

The redundant-signal RTs (45º/bright, 45º/dim, 6º/bright, and 6º/dim) were examined by a 2 × 2 repeated measures ANOVA, with the factors orientation contrast (6º, 45º) and luminance contrast (dim vs. bright). Both main effects were significant: orientation contrast [$F(1,13) = 150.4$, $p < .001$, 355 vs. 393 msec] and luminance contrast [$F(1,13) = 21.53$, $p < .001$, 364 vs. 384 msec]. Most importantly, the interaction was also significant [$F(1,13) = 33.50$, $p < .001$]. Redundant targets with two high-contrast components were responded to the fastest (353 msec); those with two low-contrast components were responded to the slowest (410 msec), and the response to those with only one high-contrast component was intermediate (356 and 375 msec for high-contrast luminance and orientation components, respectively).

In order to quantify this interaction, the mean interaction contrast (IC; see Equation 2) was calculated for each observer, and the IC values were subjected to a two-tailed t test. This test revealed the IC to be significantly greater than 0: 32.8 msec [$t(13) = 5.8$, $p < .001$], indicative of an overadditive interaction of the intensities of orientation and luminance contrast in redundant-target detection. This overadditive interaction rules out serial processing of signals from the different dimensions with any kind of stopping rule, as well as parallel processing with exhaustive search (Townsend & Nozawa, 1995). The mean RSEs for each combination of orientation × luminance intensities (45º/bright, 45º/dim, 6º/bright, and 6º/dim) were 8.3, 5.7, 5.6, and 44.1 msec, respectively, and were significantly greater than 0 in all cases [$t(13) > 2.52$].

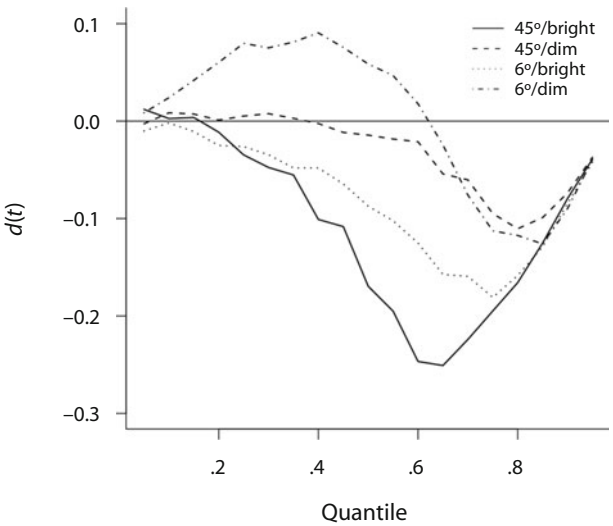

Figure 5. Violations of the race model inequality, *d*(*t*), for the four experimental conditions of Experiment 1. The different line types correspond to the different combinations of saliency in the orientation and luminance channels.

To test whether statistical facilitation in parallel models could explain the observed RSEs, violations of the RMI were analyzed. Figure 5 presents $d(t)$ for all four conditions (45º/bright, 45º/dim, 6º/bright, and 6º/dim), averaged for each 5%-quantile of the redundant-signal RT distribution. Values of $d(t)$ greater than 0 are at variance with the assumption of a parallel race architecture. For the condition with low intensity in both dimensions (6º/dim), the RMI was significantly violated in the quantile range between 0.10 to 0.20 [all ts$(13) > 2.0$, ps $< .03$]. Furthermore, for the condition with high contrast in both dimensions (45º/bright), a significant violation was found at the 0.05 quantile [$t(13) = 1.8$, $p < .05$].

Discussion

In Experiment 1, we implemented a double-factorial design combined with a redundant-signals paradigm (Townsend & Nozawa, 1995) in order to determine architecture (serial, parallel, or parallel-coactive) and a stopping rule (self-terminating or exhaustive) of the processing mechanism underlying visual search for feature pop-out targets. The intensity of target feature contrast was manipulated in two dimensions—orientation (difference of 6º and 45º, relative to vertical distractors) and luminance (dim vs. bright)—and targets were defined either singly in one dimension or redundantly in both dimensions.

The manipulation of feature contrast yielded an RT difference of around 100 msec between targets of high and low intensity. All four types of redundant target (6º/dim, 6º/bright, 45º/dim, and 45º/bright) were responded to faster than the fastest single target (defined by the relevant combination of dimension and intensity).

The mean interaction contrast of the intensity levels in redundant targets was positive and significant, excluding parallel models with exhaustive search (which would have produced an additive effect without any interaction) as well as serial models with any stopping rule (which would not have produced a significant interaction) as an explanation for the RSE. Hence, serial exhaustive models offer no viable alternative for explaining the redundancy gains that were reported by Krummenacher et al. (2001, 2002).

A superadditive interaction contrast would be observed for parallel race models with self-terminating search, as well as for coactivation models. However, significant violations of the RMI occurred over a wide range of quantiles in the 6º/dim condition and, to a lesser extent, in the 45º/bright condition—that is, in both conditions in which the intensity levels of both dimensional signal components were "equal." In the other conditions (6º/bright and 45º/dim), one dimension could be processed much faster than the other, making coactivation—although possible in principle—unlikely. Violations of the RMI rule out parallel race models as an (alternative) explanation of the observed redundancy gains.

Thus, by excluding both parallel race and serial-exhaustive models, converging evidence is provided for a coactivation model accounting for the RT redundancy gains produced by pop-out targets defined in multiple dimensions. This is in line with saliency-based models of visual search, such as

guided search (e.g., Wolfe, 1994) and dimension weighting (Found & Müller, 1996; Müller et al., 1995).

EXPERIMENT 2

The results of Experiment 1 suggest that violations of the RMI in search for singleton feature targets (Krummenacher et al., 2001, 2002) cannot be explained by a serial-exhaustive model. However, a potential account may be offered by interactive race models (Mordkoff & Yantis, 1991, 1993), which would also predict violations of the RMI if the experimental procedure generates interchannel contingencies that favor the processing of redundant relative to single signals. The key additional assumption that differentiates interactive race from independent-race (see, e.g., Raab, 1962) models is that perceptual channels are allowed to exchange information, with the strength of cross talk being proportional to the base and conditional probabilities of target signals in the respective channels. However, interactive race architectures assume that the response is triggered in parallel by two decision units (see Figures 1C and 3C). This distinguishes interactive race from coactivation models, which assume that the response is triggered by one decision unit on the basis of the integrated signals from different channels.

Information about target presence would not affect performance if the presence or absence of a feature contrast signal in one channel were uncorrelated with the presence or absence of contrast in the other channel. However, Mordkoff and Yantis (1991) described two types of contingencies that, in an interactive race model, could lead to a benefit for redundant over single targets—namely, benefits from interstimulus and nontarget response contingencies (ISC and NRC benefits). In short, the ISC and NRC benefits—which are calculated from conditional probabilities of the occurrence of signals in both channels—are measures of how much the two types of contingency in the experimental design are favoring the processing of redundant over single targets. For example, if the conditional probability of a target's being present in one channel, given the absence of a target in another channel, is higher than the base probability of target presence, target detection is faster if there is cross talk between the channels. Before introducing how these two types of contingencies can be formulated, we will briefly review the results of Mordkoff and Yantis (1991, 1993).

Mordkoff and Yantis (1991) showed that, in a divided-attention paradigm in which target letters could appear at one or at both of two locations, contingencies predicted whether or not violations of the RMI were observed. In particular, violations of the RMI were obtained when there were either interstimulus, nontarget response, or both types of contingency. No violations of the RMI occurred when the contingencies were 0. In order to create zero-contingency conditions, Mordkoff and Yantis (1991) presented two nontarget items—a manipulation that allowed for the independent manipulation of the two types of contingencies.

In Mordkoff and Yantis (1993), observers were presented with one stimulus at a fixed location on each trial and made a target-present response when the display contained a prespecified color, a prespecified letter, or both target-defining features. Even though there were no contingencies in the experimental design favoring redundant- over single-signal trials, Mordkoff and Yantis (1993) found significant violations of the RMI, indicating that color and form were processed coactively rather than according to an independent- or an interactive race model. However, this finding does not extend to the question of saliency summation in visual search, for several reasons: First, Mordkoff and Yantis's (1993) paradigm did not involve any search component, since there was no uncertainty about the target location; second, correct responses required the identification of object features—in contrast with the detection of feature singletons as was required in the present study, in which responses could be based solely on the "featureless" activation of units in the salience map. Thus, Mordkoff and Yantis (1993) were interested in redundancy gains in object identification rather than in the summation of feature contrast into a salience map. The same arguments apply to a study by Feintuch and Cohen (2002), in which observers also had to perform an object identification task, with targets defined by a certain color, a certain form, or both. Both the Mordkoff and Yantis (1993) and the Feintuch and Cohen studies indicated that there are postselective processes whose outputs are integrated in a coactive fashion. Indeed, it is likely that coactive processing architectures are implemented from early sensory through postselective to motor stages of processing (see, e.g., Miller, 2007). However, the demonstrations of coactive processing at postselective stages of object identification do not bear on the current question at issue—namely, whether there would also be coactive coding of search-guiding signals at preattentive processing stages, as is assumed by salience summation models.

Interstimulus and Nontarget Response Contingencies

According to Mordkoff and Yantis (1991), there are two types of contingency that might result in "benefits" for redundant relative to single targets: ISC and NRC (see Mordkoff & Yantis, 1991, for an in-depth discussion).

ISCs. For determining ISCs potentially favoring the processing of redundant over single signals, it is useful for one to reiterate how search displays that may contain a pop-out target defined redundantly in two dimensions are processed in a parallel architecture (with or without cross talk). There are two processors of feature contrast, one for each of the two possible dimensions. If no target is present, both channels signal the absence of feature contrast. If the display contains, say, an orientation target, one processor signals the presence of feature contrast, and the other signals the absence after the respective (present or absent) criteria are reached in the two channels.

A display that generates a feature contrast signal in the orientation dimension (in response to an orientation or a redundant target) may be denoted as T^O, and a display that generates no feature contrast signal in the luminance dimension as N^L. Then, the conditional probability that a display generates a feature contrast signal in the orientation dimension, given the absence of luminance contrast,

is $P(T^O|N^L)$. If the probability of a display with a feature contrast in the orientation dimension, given that there is no feature contrast in the luminance dimension, is higher than the probability of a display containing an orientation feature contrast [i.e., $P(T^O|N^L) > P(T^O)$], then cross talk from the luminance channel to the orientation channel would facilitate the detection of a target. In Experiment 1, the contingencies were chosen so as to result in $P(T^O) = .2$—that is, less than $P(T^O|N^L) = .33$. Thus, the information that no feature contrast is present in the luminance channel would be beneficial for the detection of feature contrast in the orientation channel. Conversely, if $P(T^O|N^L)$ were greater than $P(T^O)$, cross talk between both channels would be detrimental to the detection of a feature contrast signal in the orientation channel. Mordkoff and Yantis (1991) quantified this relationship as the ISC:

$$\mathrm{ISC}(N \Rightarrow T) = P(T^O|N^L) - P(T^O), \tag{5}$$

where N represents target-absent displays, and T represents target-present displays. If the value of $\mathrm{ISC}(N \Rightarrow T)$ is positive, cross talk facilitates target detection; if it is negative, target detection is inhibited by between-channel cross talk. Analogously, potential contingencies between channels that both contain a target are given as follows:

$$\mathrm{ISC}(T \Rightarrow T) = P(T^O|T^L) - P(T^O), \tag{6}$$

where $P(T^O|T^L)$ is the probability that a feature contrast is present in the orientation dimension, given that there is a feature contrast in the luminance condition.

If the benefit for target detection given that target presence has been detected in the other channel [$\mathrm{ISC}(T \Rightarrow T)$] is greater than the benefit given that target absence has been determined in the other channel [$\mathrm{ISC}(N \Rightarrow T)$], the ISCs favor the processing of redundant relative to single signals. In other words, $\mathrm{ISC}(N \Rightarrow T)$ benefits performance on single-signal trials, and $\mathrm{ISC}(T \Rightarrow T)$ benefits performance on redundant-signal trials. If $\mathrm{ISC}(T \Rightarrow T)$ is greater than $\mathrm{ISC}(N \Rightarrow T)$, redundant-signal trials exhibit an advantage relative to single-signal trials. The interstimulus contingencies benefit (ISCB) favoring redundant- over single-signal trials can be quantified as:

$$\mathrm{ISCB}(N) = \mathrm{ISC}(T \Rightarrow T) - \mathrm{ISC}(N \Rightarrow T). \tag{7}$$

Mordkoff and Yantis (1991) proposed that these contingency benefits are proportional to the baseline and conditional probabilities. As an illustration, they suggested that the baseline activity of one channel is proportional to the average frequency of target presence in that channel. The strength of cross talk according to their model is also proportional to the ISCs. For example, if there is an $\mathrm{ISC}(N^L \Rightarrow T^O)$ of .16 (i.e., the conditional probability of feature contrast in the orientation dimension given no feature contrast in the luminance dimension is greater than the baseline probability of targets defined by orientation contrast) and the luminance processor is 75% certain that no luminance contrast is present, the luminance channel could add .12 (arbitrary) units of activity to the orientation channel—that is, its level of certainty multiplied by the contingency benefit: $.75 * .16$ (T. Mordkoff, personal communication, Dec. 17, 2008). Consequently, Mordkoff and Yantis's (1991) model predicts the RSE and violations of the RMI to be larger, the larger the ISCB.

NRCs. According to Mordkoff and Yantis (1991), a second mechanism by which cross talk between channels might yield a benefit for redundant- over single-signal trials is given by NRCs, in which the (unconditional) probability of a target-present response is related to that of a target-present response, given that one channel signals the absence of a feature contrast. One could question whether NRCs are a concept that is fit for search situations with more than two simultaneously presented items. However, what is relevant here is only the probability of having to make a target-present response, rather than that of having to selectively attend to a particular location. This is because our extension of the Mordkoff and Yantis (1991) logic to search situations assumes a simple, binary present-absent-response decision made on the basis of activity on the saliency map, rather than an n-way decision selecting one out of n locations (see Figures 1 and 3). From the fact that the conditional probability of a target-present response (given that target absence is signalled in one of the two channels) is higher than the baseline (unconditional) probability of a target-present response, it follows that interchannel cross talk facilitates the detection of a target. If the (unconditional) probability of a target-present response were greater than the probability of a target-present response, given that target absence is signalled in one channel, there would be inhibition on single-signal trials. Redundant-signal trials, by contrast, would not be subject to such inhibition. The benefit for redundant- relative to single-signal trials in the case of an NRC (NRCB) can be formalized as

$$\mathrm{NRCB}(N^O) = P(+) - P(+|N^O), \tag{8}$$

where $P(+)$ is the probability of a target-present response, and $P(+|N^O)$ the probability of a target-present response given that no feature contrast has been detected in the orientation dimension. In Experiment 1, the probability of a target-present response was .6, and the probability of a target-present response given that no feature contrast was present in the orientation dimension was .33; that is, there was a benefit for redundant- relative to single-signal trials [$\mathrm{NRCB}(N^O) = .27$].

Rationale of Experiment 2

Mordkoff and Yantis (1991, 1993) eliminated contingencies by increasing the nontarget stimulus set: Instead of having only one stimulus defined as a nontarget, they introduced a second nontarget stimulus, thereby rendering both ISCB and NRCB 0. However, in visual search for singleton pop-out targets, there is only one type of nontarget trial—displays that contain only distractors—so the possibilities for manipulating the contingency benefits are more limited. Because the contingency benefits depend on the conditional probabilities of luminance and orientation feature contrasts, we could manipulate only the ratio of target-present to target-absent trials and of single- to redundant-target trials. Figure 6 illustrates the contingency benefits ISCB and

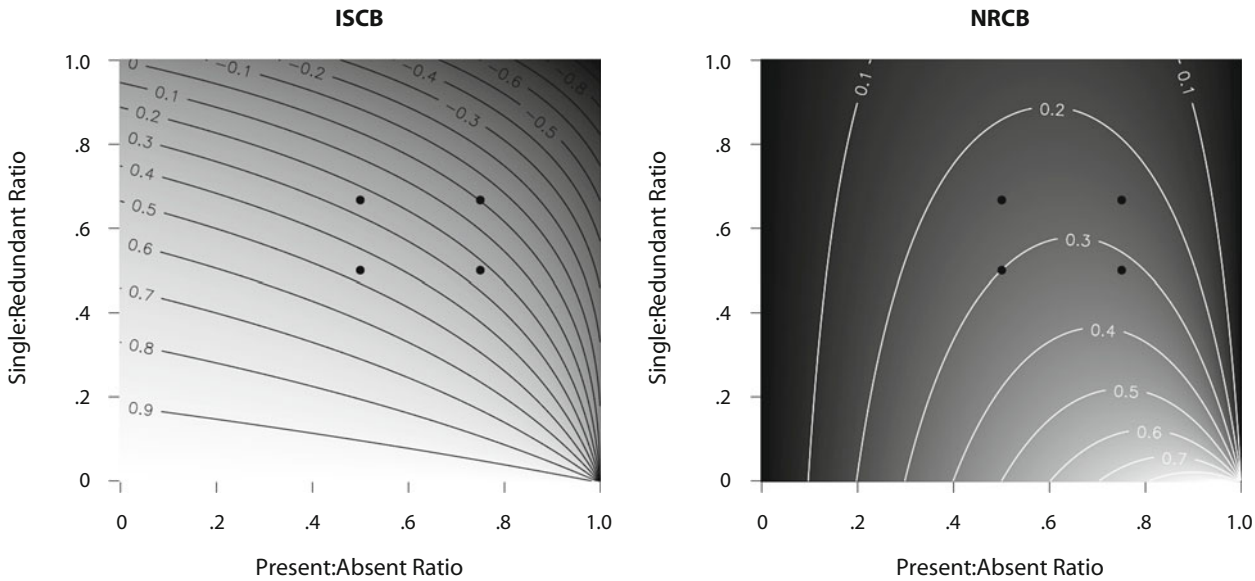

Figure 6. (A) Interstimulus contingency benefits (ISCBs) and (B) nontarget response contingency benefits (NRCBs) dependent on the ratios of target-present to target-absent (abscissa) and single-target to redundant-target (ordinate) trials. The contingency benefits are represented in different levels of gray, with white corresponding to 1 and black to −1 (in the case of ISCB) and 0 (in the case of NRCB). Additionally, the contour lines represent the course of change in ISCB and NRCB values. The black dots represent the four contingency conditions examined in Experiment 2.

NRCB for different ratios, between 0 and 1, of present to absent targets and, for target-present trials, of single to redundant targets. As can be seen from the figures, these manipulations make it possible to create conditions with no ISCB (i.e., ISCB is 0). Since cross talk in the interactive race model is affected proportionally by the contingency benefits (Mordkoff & Yantis, 1991; T. Mordkdoff, personal communication, Dec. 17, 2008), the RSE and the amount of violations of the RMI would consequently be proportional to the contingency benefits favoring redundant over single targets (ISCB and NRCB). Given this, Experiment 2 was designed to test whether the RSE and the amount of violations of the RMI are indeed proportional to ISCB and NRCB (as is expected on the interactive race model).

Thus, in order to test saliency summation against interactive race models, the ratios of target-present to target-absent trials (1:1 vs. 3:1) and, for target-present trials, the ratio of single to redundant targets (2:1 vs. 1:1) were manipulated as between-subjects factors. For each of the four experimental conditions, the ratios of target-present to target-absent trials and single-target to redundant-target trials (as well as the corresponding benefits from ISCBs and NRCBs) are presented in Table 1. Note that the ratios in Table 1 correspond to the black dots in Figure 6, with the present-to-absent ratios of 1:1 and 3:1 corresponding to values of .5 and .75 units of the *x*-axis scale, and the single-to-redundant ratios of 2:1 and 1:1 to values of .67 (=2/3) and .5 units on the *y*-axis scale. The frequencies of single-, redundant-, and absent-target trials for each condition are presented in Table 2.

If an interactive race model were to explain the redundancy gains and violations of the RMI, the RSE and violations of the RMI would be predicted to be larger, the larger the contingency benefits (ISCB and NRCB). In contrast, saliency summation models (see, e.g., Krummenacher et al., 2001, 2002; Müller et al., 1995; Wolfe, 1994) predict the RSE and violations of the RMI to be insensitive to manipulations of signal contingencies, because they assume that violations of the RMI reflect the integration of different dimensional feature contrast signals into a common master saliency representation.

Method

Participants. Sixty-four observers took part in Experiment 2 (20 male; 3 left-handed; age range, 19–47 years, median age, 24.0 years).

Stimuli and Timing. The stimuli and timing were the same as in Experiment 1, except that only high-intensity targets were presented (orientation contrast 45º from the vertical, luminance contrast matched to 45º orientation contrast; based on the data obtained in Experiment 1). Displays contained either no target, a target defined in one dimension (orientation or luminance), or a redundant target (defined by both orientation and luminance).

Design and Procedure. Experiment 2 took about 1 h to complete. The session started with a practice block of 30 trials (data excluded from analysis). The main experiment consisted of 23 blocks of 60 trials each, giving a total of 1,410 trials. The ratio of target-present to target-absent displays (1:1 vs. 3:1) was varied; additionally, for target-present trials, the ratio of single to redundant targets was varied (single-to-redundant ratios of 2:1 vs. 1:1; see Table 2). Each observer was randomly assigned to one of the four possible combinations of present:absent ratio × single:redundant ratio. The resulting contingencies for each condition are given in Table 1.

Results

The data were analyzed in two steps. First, we examined whether the RSE and violations of the RMI could be replicated under the different contingency conditions (ISC and NRC) of Experiment 2. Second, we assessed the (observed) RSE and violations of the RMI with respect to

Table 1
Contingency Benefits ISCB and NRCB for Each of the Four Experimental Conditions Resulting From Crossing the Factors (Target) Present-to-Absent and Single-to-Redundant (Target) Ratio

Experimental Condition	Present-to-Absent Ratio	Single-to-Redundant Ratio	ISCB	NRCB	RSE (msec)	Area Under $d(t)$
1	1:1	2:1	.25	.25	19.7	−13.7
2	1:1	1:1	.47	.30	20.0	−14.9
3	3:1	2:1	0	.25	17.7	−19.8
4	3:1	1:1	.24	.32	14.8	−22.2

Note—The single-to-redundant ratio is presented in the form of a:b, where a and b represent the numbers of single and redundant targets, respectively. ISCB, interstimulus contingencies benefit; NRCB, nontarget response contingencies benefit; RSE, redundant-signals effect.

the predictions of interactive race models; that is, would the two measures positively depend on the contingency benefits ISCB and NRCB? Trials with RTs of less than 200 msec (i.e., anticipatory responses, <0.1% of all trials) were excluded from further analysis.

Error analysis. The overall error rate was low: 0.2% misses and 4.3% false alarms. Since the miss rates were below 1% for all of the conditions, only false alarms were analyzed further. A 2 × 2 ANOVA with the factors present:absent ratio (1:1 vs. 3:1) and single:redundant ratio (2:1 vs. 1:1) revealed only the main effect of the present:absent ratio to be significant [$F(1,60) = 33.9$, $p < .001$], with 1.5% false alarms in the 1:1 condition and 7.2% in the 3:1 condition.

Mean RT analysis. The RT data for single- and redundant-signal trials are presented in the left- and right-hand panels of Figure 7, respectively. Individual observers' mean RTs were subjected to a 3 × 2 × 2 ANOVA, with the within-subjects factor target type (orientation, luminance, redundant) and the between-subjects factors present:absent ratio and single:redundant ratio. This ANOVA revealed the main effects of target type and present:absent ratio to be significant: target type [$F(2,120) = 159.85$, $p < .001$], with RTs of 349, 345, and 322 msec for luminance, orientation, and redundant targets, respectively; and present:absent ratio [$F(1,60) = 4.76$, $p < .033$], with target-present RTs of 348 and 330 msec for the 1:1 and 3:1 present:absent conditions, respectively. That is, redundant targets were responded to 22.8 msec faster than were nonredundant targets, and targets were responded to 18.0 msec faster in the 3:1 than in the 1:1 present:absent ratio condition. Importantly, neither the main effect of single:redundant ratio nor any of the interactions involving this factor were significant ($0.51 \leq F \leq 0.62$). Post hoc comparisons of the different target types by means of Tukey's HSD post hoc test revealed all pairwise comparisons to be significant (all ps $< .03$): RTs were 4 msec faster to orientation than to luminance targets, and redundant targets were detected faster (by 22 and 27 msec) than were luminance and orientation targets, respectively.

RT distribution analysis. Figure 8 displays the results of the tests for violations of the RMI—that is, $d(t)$ (see Equation 4)—for the four conditions of Experiment 2. The number of observations for estimating the CDFs for each target type in each condition ranged from 147 to 507, with a median of 249 (which is well above the 20 observations minimally required, according to Kiesel et al., 2007). In order to not overestimate violations of the RMI owing to multiple t tests performed on the same data set (see Kiesel et al., 2007), only quantiles in the range from 0.05 to 0.20 were examined. With a present:absent ratio of 1:1, there were significant violations at all tested quantiles [all ts$(15) > 2.8$, ps $< .04$] for both single:redundant ratio conditions. In the 3:1 present:absent and 2:1 single:redundant ratio conditions, significant violations were evident at the 0.10 and 0.15 quantiles [both ts$(15) > 1.9$, ps $< .04$]. And, in the 3:1 present:absent and 1:1 single:redundant ratio conditions, there was a tendency toward a violation at the first quantile [$t(15) = 1.3$, $p < .10$].

Analysis of contingency benefits. The analyses conducted thus far revealed substantial redundancy gains and violations of the RMI. The purpose of Experiment 2 was to test whether an interactive race model (Mordkoff & Yantis, 1991) could account for this data pattern. The in-

Table 2
Occurrence of Target Types in Experiment 2 per 120 Trials for the Four Experimental Conditions (See Table 1)

Orientation	Luminance N^L	Luminance T^L
	Condition 1	
N^O	60	20
T^O	20	20
	Condition 2	
N^O	60	15
T^O	15	30
	Condition 3	
N^O	30	30
T^O	30	30
	Condition 4	
N^O	30	22.5
T^O	22.5	45

Note—T^O and N^O denote the presence and absence, respectively, of an orientation feature contrast signal, and T^L and N^L the presence and absence, respectively, of a luminance feature contrast signal. That is, displays containing no target at all are denoted by N^O and N^L. Single luminance targets, for example, are denoted by T^L and N^O, whereas redundant targets are denoted by T^L and T^O (see Appendix B for details).

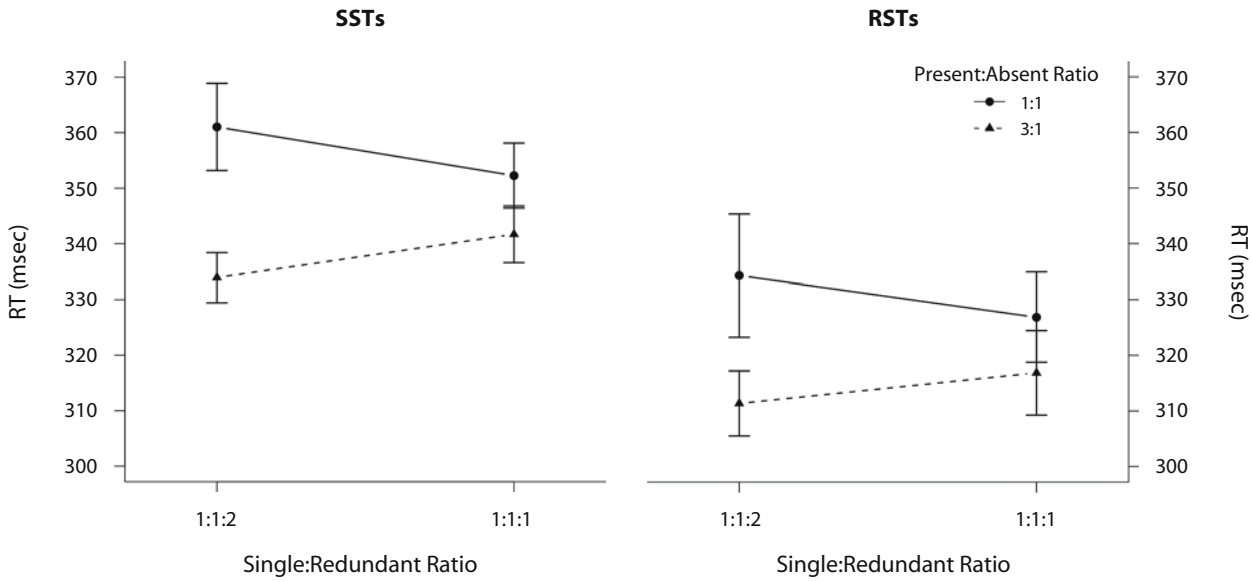

Figure 7. Mean reaction times (RTs) for single-signal trials and redundant-signals trials in Experiment 2.

teractive race model predicts that both the size of the RSE (mean RTs) and the magnitude of RMI violations increase with contingencies increasingly favoring redundant relative to single targets. (See Table 1 for the contingencies in the four experimental conditions of Experiment 2.)

In order to test whether the two types of contingency benefits had an effect on the size of the RSE and of the amount of violations of the RMI, we conducted separate ANOVAs of the two dependent measures, RSE and the area under $d(t)$, each with the factor of either ISCB or NRCB. For the ANOVAs of the RSE, neither ISCB [$F(3,60) = 1.9, p < .14$] nor NRCB [$F(2,61) = 2.6, p < .09$] yielded a significant effect. Similarly, for the area under $d(t)$, the effects of neither ISCB [$F(3,60) = 1.8, p < .16$] nor NRCB [$F(2,61) = 1.6, p < .21$] were significant.

Although the effect of NRCB was not statistically reliable, we further examined conditions 1 and 4, for which the ISCB was near identical (.25 vs. .24), but which differed in the NRCB (.25 vs. .32). An interactive race model would predict the RSE [and the area under $d(t)$] to be greater in condition 4 than in condition 1, since the nonresponse contingency benefit is greater with a similar ISCB (given that, on such a model, contingencies proportionally affect the amount of cross talk; see Mordkoff & Yantis, 1991). However, if anything, the opposite is the case: Numerically, both the RSE and the area under $d(t)$ are smaller rather than larger in condition 4 than in condition 1; planned (two-sided) comparisons revealed the difference to be (borderline) significant for both the RSE [$t(30) = 1.8, p < .08$] and the area under $d(t)$ [$t(30) = 2.3, p < .02$]. That is, the RSE and area under $d(t)$ were reduced for conditions with 75% targets, as compared with conditions with 50% targets—the opposite of what would be expected on the interactive race model. This pattern may be due to a more liberal response criterion with more frequent targets, resulting in shorter decision times (as compared with less frequent targets). And, with shorter decision times, saliency modulations—such as increased salience owing to redundant target definition—have been demonstrated to yield smaller RT effects (for details, see Zehetleitner & Müller, 2009).

Given the aforementioned finding that the NRCB does not contribute to violations of the RMI in an interactive race model of redundant-target search, a closer examination of condition 3—in which the ISCB was 0—becomes possible. According to the interactive race model, processing in this condition should not differ from an independent-race model due to the lack of contingency benefits, so there should be no violations of the RMI. However, in condition 3, the RMI was violated at the .10 and .15 quantiles (see above). It follows that these RMI violations cannot be accounted for by interactive race model architectures. Note that this exclusion is not based on null results, because with NRCBs, the amount of the RMI violations was significantly larger the smaller the NRCB, whereas interactive race models would predict the opposite. Furthermore, with respect to the ISCB, there were significant violations of the RMI in condition 3 in which the ISCB was 0—a case for which interactive race models would not predict any violations of the RMI at all.

Discussion

In Experiment 2, we replicated the finding of significant redundancy gains for singleton targets defined by feature contrasts in two dimensions, as compared with targets defined by contrast in only one dimension (Krummenacher et al., 2001, 2002). These gains cannot be explained by statistical facilitation (Raab, 1962), because the RMI violations were significant in Experiment 2. Importantly, neither the size of the mean RT redundancy gains nor that of the RMI violations [i.e., the area under $d(t)$] increased with contingencies increasingly favoring redundant over single

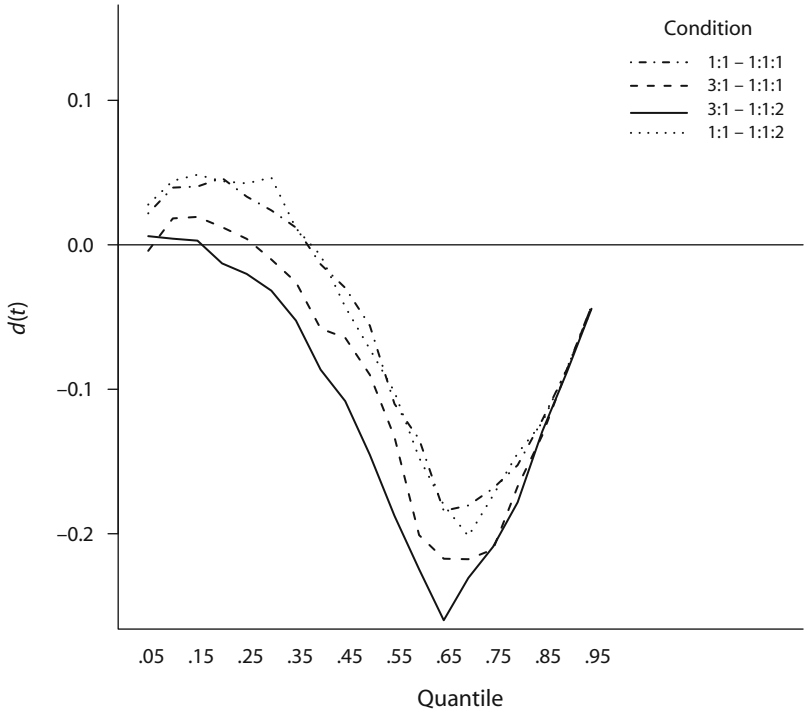

Figure 8. Violations of the race model inequality for the four experimental conditions of Experiment 2. The different line types represent the four experimental conditions of the present-to-absent ratio (1:1 vs. 3:1) and the single-to-redundant ratio (1:1:1 vs. 1:1:2).

targets. Although interactive race models can theoretically explain violations of the RMI, they predict an increase in the size of the violations as the contingencies become stronger, which was clearly not the case in Experiment 2.

Thus, by excluding interactive race models, the findings of Experiment 2 provide further support for the category of model assuming the existence of a master saliency representation integrating dimension-based feature contrast signals (Müller et al., 1995; Wolfe, 1994). The findings also corroborate the interpretation of the mean RT redundancy gains and RMI violations proposed by Krummenacher et al. (2001, 2002), namely in terms of coactive processing.

GENERAL DISCUSSION

The present study was designed to examine whether RT redundancy gains and violations of the RMI in visual search for singleton feature targets could be explained by coactivation models, such as guided search (e.g., Wolfe, 1994) or dimension weighting (Müller et al., 1995), which assume the integration of dimension-specific feature contrast signals onto a common (supradimensional) saliency representation driving the allocation of focal attention. Although many current models of visual search assume saliency summation, surprisingly, to date, there has been no neurophysiological and little behavioral evidence in support of this assumption. To address this situation, in the present study, models of coactive processing were compared with two alternative types of architecture: serial models assuming exhaustive search across dimensions (Townsend & Nozawa, 1997), and interactive race models (Mordkoff & Yantis, 1991) allowing for cross talk and thus the exchange of dimension-based information between channels. In recent literature, violations of the RMI in visual search for singleton feature targets have generally been taken as an indicator of coactive processing of dimension-based signals (e.g., Koene & Zhaoping, 2007; Krummenacher et al., 2001, 2002; Turatto et al., 2004). However, this is without any empirical evidence ruling out alternative models.

Implications for Saliency Summation Models

By ruling out such alternative models, the results of the present experiments have important implications for theories of selective processing assuming integration of multiple dimensional signals into a common representation (see, e.g., Itti & Koch, 2000; Müller et al., 1995; Wolfe, 1994). In particular, in Experiment 1, we examined whether serial-exhaustive models (Townsend & Nozawa, 1997) could account for violations of the RMI in visual search for redundant feature singletons. In a double-factorial design (Townsend & Nozawa, 1995), serial-exhaustive models predict a very specific subadditive interaction when manipulating the intensity of feature contrast within the two dimensions of a redundant target. However, the results demonstrated a superadditive interaction, which rules out serial models with any stopping

rule, and instead is consistent with parallel (independent- and interactive race) and coactivation models. Interactive-race models, on which the two processing channels are able to interact with each other, could in principle also account for violations of the RMI (Mordkoff & Yantis, 1991). However, the results of Experiment 2 showed that both the RSE as well as the magnitude of RMI violations were independent of ISCs and NRCs, effectively ruling out interactive race models of processing in visual search for (redundantly defined) singleton feature targets.

Whereas the present study investigated whether violations of the RMI in visual pop-out search would be accounted for by coactivation or alternative models, the issue of at what processing stage RMI violations (indicative of coactivation) arise has been addressed in other studies (Krummenacher et al., 2001, 2002; Töllner, Zehetleitner, Krummenacher, & Müller, in press). Specifically, the question at issue in these studies was whether coactivation indeed occurs at an early, preattentive stage of salience computation, or at a later, postselective stage in which a stimulus is analyzed and translated into a response. Although the latter cannot be definitely ruled out, there is a growing body of evidence that fits nicely with a salience, but not a decisional (or motoric), origin of coactivation effects. Krummenacher et al. (2002) demonstrated that RMI violations depend on the redundant-target signals being in close spatial proximity: either at the same location, as in the present study, or—as in the case of dual (cross-dimensional) feature singletons examined by Krummenacher et al. (2002)—at directly adjacent locations. When the two target singletons were placed further apart, Krummenacher et al. (2002) still observed mean redundancy gains, but no violations of the RMI. Additionally, Krummenacher et al. (2002) found violations of the RMI when the two adjacent singletons were defined in two different dimensions, but not when they were defined (by different features) within the same dimension. This pattern of results argues in favor of coactivation taking place at the level of the salience map, which has a topographical organization and integrates dimension-specific rather than feature-specific contrast signals in a spatially scaled fashion.

Furthermore, in another experiment in which spatial attention was symbolically precued to a specific quadrant (2×2 locations) of the search display, Krummenacher et al. (2002) found violations of the RMI not only when the (redundant) target appeared at one of the precued locations (which was the case in 79% of the trials), but also—and even more markedly—when it appeared within another display quadrant (which happened on only three quadrants $\times$ 7% of the trials). This pattern is consistent with a preattentive rather than a postselective origin of coactivation. Consistent with this pattern, in a recent electrophysiological study of visual search for redundantly defined singleton targets, Töllner et al. (in press) found redundant targets to produce faster latencies of the N2pc (a negative-going deflection with a maximum over visual areas of the hemisphere contralateral to the location of an attended stimulus) component as compared with those of singly defined targets, whereas there was no difference in the (response-related) lateralized readiness potential. Since the N2pc is taken to be a marker of the transition from the preattentive perceptual coding of the whole search array to the focal-attentional processing of selected (target) stimuli (see, e.g., Eimer, 1996; Hopf, Boelmans, Schoenfeld, Heinze, & Luck, 2002; Töllner, Gramann, Müller, Kiss, & Eimer, 2008; Woodman & Luck, 1999), this pattern is indicative of a preattentive, perceptual origin of coactivation rather than of a postselective response-related origin—whether the latter is assumed to involve processes operating at the stimulus analysis and stimulus-to-response mapping stages (e.g., Feintuch & Cohen, 2002) or the motor-response stage (e.g., Miller, 2007).

Thus, taken together with the previous work, the present study provides strong support for saliency map models—an instance of coactivation models—of processing in visual search for singleton feature targets. That is, by excluding alternative processing architectures that could, in principle, also account for previous findings (e.g., those of Krummenacher et al., 2001), the present results critically augment the behavioral evidence in favor of the assumption of saliency summation, which is central to many current models of visual search. Finally, although this body of evidence indicates that there is coactivation occurring at the stage of salience computation (affecting the speed of focal-attentional selection), this does not logically exclude the possibility that there may also be coactive processing occurring at later processing of stimulus analysis, stimulus-to-response mapping, and/or motor programming.

Implications for Other Processing Stages

As was considered previously, in principle, coactive processing is possible at various stages of processing, from the initial coding of properties within (e.g., visual dimensions: Koene & Zhaoping, 2007; Krummenacher et al., 2001, 2002; Turatto et al., 2004) and across (e.g., Miller, 1982) sensory modalities through the stages of object identification and response selection (e.g., Feintuch & Cohen, 2002; Mordkoff & Yantis, 1993) to that of motor processing (e.g., Miller, 2007). However, models that adequately describe processing at one particular stage do not necessarily generalize to other stages of processing. In principle, at all processing stages, violations of the RMI can be indicative of coactivation, but also of serial-exhaustive processing and processing along the lines of parallel interactive race models. Consequently, to argue in favor of coactivation models for any of these processing stages, the alternative processing architectures have to be excluded. This can be achieved by using the double-factorial design that was suggested by Townsend and Nozawa (1995) for testing serial-exhaustive models and the manipulation of interstimulus and nontarget response contingencies that were suggested by Mordkoff and Yantis (1991) for testing interactive race models.

For the latter test, the present study provides a new methodological approach: Mordkoff and Yantis (1991) suggested putting the interactive race model to test by completely removing (from the experimental design) any contingencies that can benefit the processing of re-

dundant over single signals. If RMI violations are still observed, these cannot be accounted for by their interactive race model. However, there are situations in which it is not possible to completely remove the contingency benefits—for example, when, due to the nature of the experimental paradigm, there can be only one target-absent stimulus (such as in visual search detection tasks). For this case, we suggest instead manipulating the strength of the contingencies and examining whether the magnitude of the RSE and of the violations of the RMI covary with this strength manipulation.

Arguably, for the postselective stages of processing mentioned previously, it remains an open issue whether processing is really coactive. Thus, for instance, for the stage of (visual) object identification, Mordkoff and Miller (1993) could exclude interactive race models as an account for the observed violations of the RMI. However, serial-exhaustive models are still an alternative, which could also—in addition to coactivation models—explain the RMI violations. By contrast, serial-exhaustive models have been tested and could be excluded in a multimodal (audiovisual) simple-RT paradigm (Patching & Quinlan, 2004), but a test of the interactive race model has yet to be carried out, either by removing contingency benefits completely (as was suggested by Mordkoff & Yantis, 1991) or by parametrically modulating their strength (as was suggested in the present study).

Conclusion

In summary, the present study provided important—and hitherto lacking—evidence in support of the saliency summation assumption made by influential models of visual search (see, e.g., Found & Müller, 1996; Itti & Koch, 2000; Wolfe, 1994) in ruling out possible alternative architectures of serial-exhaustive and parallel interactive race type processing.

Furthermore, the present study provided a novel method to test interactive race models: In situations in which it is not possible to completely eliminate contingency benefits favoring redundant- over single-signal trials, parametric modulation of these contingencies permits examining whether the magnitude of the RSE and the amount of RMI violations do covary with these contingencies, as is predicted by the interactive race model.

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NOTES

1. This was affirmed in personal communications with Jacqueline Gottlieb (Dec. 16, 2008), Jeremy Wolfe (Dec. 15, 2008), and Laurent Itti (Dec. 15, 2008).

2. There is also evidence suggesting that feature identity is derived preattentively and can be transferred into working memory quite rapidly, within some tens of milliseconds (J. Johnston & Pashler, 1990). However, it remains possible that what J. Johnston and Pashler referred to as an "attention-calling interrupt signal" can trigger a (direct) detection response if feature information is irrelevant, as well as the allocation of focal attention, which is necessary for transferring feature identity information into working memory.

APPENDIX A

To demonstrate that the race model inequality (RMI) can be applied to visual-search situations, it is useful for one to reconsider and formalize the decision process. As soon as activity of a master map detection unit exceeds a certain boundary at some location, this location can be attentionally selected and/or a detection response can be triggered.

The time required for the first local (master map) detection unit to exceed the boundary a can be conceived of as a random variable X and expressed as the minimum of the times required by any (location) units to exceed a threshold:

$$X = \min(X_1^A, \ldots, X_j^T, \ldots, X_n^A), \tag{A1}$$

where n is the number of items in the display, and X_i^A and $X_{j\neq i}^T$ denote a random variable for a distractor and, respectively, a target item at location i to exceed the boundary; and $T \in \{C, O, CO\}$, where C, O, and CO denote color-defined, orientation-defined, and (redundant) color-plus-orientation-defined targets, respectively.

First of all, for the time of a target to exceed a certain boundary, its exact location is irrelevant—that is:

$$X = \min(X^T, X_1^A, \ldots, X_{n-1}^A). \tag{A2}$$

Second, on target-absent trials, false positive responses are triggered extremely rarely (typically ~3%), so that most of the time, $X_i^A = \infty$; that is, a distractor item effectively never exceeds the target-present boundary a. Consequently,

$$X = \min(X^T, \infty, \ldots, \infty) = X^T; \tag{A3}$$

that is, the overall time of one target among $n-1$ distractors to exceed boundary a is independent of the set size, which is an important characteristic of efficient search. To ensure that the transition from Equation A2 to Equation A3 is valid even in case of a small fraction of false positive responses (anticipations), it is necessary to remove the distributions of anticipations from the RT distributions (using a kill-the-twin procedure, which for each false-alarm RT removes a hit of the same RT; see, e.g., Eriksen, 1988).

For X^T, a parallel race model makes the assumption that $X^{CO} = \min(X^C, X^O)$, on which the RMI is predicted to hold. Violations of the RMI could then be interpreted in terms of coactivation at the level of the (master map) decision units.

Note that these considerations describe the time until activity on the salience map exceeds a given threshold, independently of whether the detection response is made directly on the basis of that fact or whether attentional selection is assumed to be a necessary precondition for the triggering of a detection response.

APPENDIX B
Display Size Control Experiment

A control experiment was designed to test whether the targets with low intensity levels in Experiments 1 and 2 (6º orientation and matched luminance level) give rise to efficient, parallel search, or whether they are processed in an inefficient, serial manner. To examine whether low-intensity targets are processed efficiently (i.e., "pop out" of the display), the display size was varied, ranging from 16 to 36 elements. The criterion for "pop-out" was a slope of the search function relating display size to a reaction time (RT) of less than 5 msec/item. As in Experiment 1, luminance targets were adjusted so as to produce RTs similar to those for orientation targets.

Method

Participants. Eight observers took part in the control experiment (3 male, 1 left-handed, age range 19–29 years, median age 22.5 years), which took half an hour to complete.

Stimuli and Timing. Search displays comprised 16, 25, or 36 items, arranged in 6×6, 5×5, and 4×4 rectangular arrays, respectively.

Design and Procedure. The experiment consisted of 10 blocks of 60 trials each. In half of the experimental trials, no target was presented (target-absent trials). Orientation and luminance targets were equally frequent on target-present trials. For each observer, the session consisted of 1 practice block, 2 blocks in which the intensity of the luminance target was adjusted in order to produce RTs that did not differ from those for the 6º orientation target, and 7 (experimental) blocks in which display size was varied randomly from trial to trial. In Block 2, only orientation targets were presented, and the median of target-present RTs was calculated online. In Block 3, target-present trials contained luminance targets only, with the target luminance being adjusted in an adaptive staircase procedure (see Experiment 1). During the final 7 blocks, the luminance was kept constant at the value returned by the staircase procedure (ranging from 15 to 25 cd/m^2), and display size was varied randomly between 36, 25, and 16 items.

Results and Discussion

Search slopes were 3.1 msec/item (luminance) and 1.7 msec/item (orientation), with intercepts of 403.1 msec and 407.2 msec, respectively. An ANOVA of the RTs with the factors target type (luminance or orientation) and display size (16, 25, or 36 items) revealed both main effects to be significant: dimension [$F(1,7) = 5.68$, $p < .049$] and display size [$F(2,14) = 16.3$, $p < .001$] [interaction, $F(2,14) = 1.9$, n.s.]. Two separate comparisons (paired-samples t tests) of the intercepts and slopes of the search RT/display size functions between the two dimensions revealed no significant differences [$t(7) = -1.8$, $p < .12$] (slope: 3.1 msec/item and 1.7 msec/item for luminance and orientation, respectively) and [$t(7) = 0.21$, $p < .8$] (intercept: 403 and 407 msec for luminance and orientation, respectively). Neither slope was significantly larger than 3 msec/item—a slope reported by Treisman and Gelade (1980) for feature singletons (both ts < 0.2, $p > .8$). That is, performance was characterized by the same intercept, but numerically different (though "efficient") slopes for the two dimensions. Although the difference in search rates per item was not significant, it led to a statistically reliable difference in mean RTs. This indicates that, for some unknown reason, the staircase procedure failed to provide luminance values that exactly matched the 6º tilt of the orientation targets. However, even with this underestimation of the luminance values (which was not present in Experiment 1, in which there was no significant effect of dimension), the slopes were shallow.

The shallow search slopes (<5 msec/item) show that the low-intensity targets used in Experiments 1 and 2 could be detected efficiently. Thus, an orientation contrast between targets and distractors of 6º and a correspondingly low luminance contrast can be used as a manipulation of intensity in a double-factorial design, while still yielding an efficient pop-out search, which was a prerequisite for the critical tests in Experiment 1.

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