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Learning to shield visual search from salient distractors

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General Introduction

In our everyday life, we search all the time. We spend a lot of time searching for our keys, our reading glasses or a subway stop. Visual searches are the most prominent task the visual system has to cope with (Wolfe, 1998). Imagine searching for the book you are reading. If the book happens to lay on your bed, the search is quite easy: it pops out from its environment. But if the book is on the bookshelf among many other books, the search is comparably hard. In the 1980's, Anne Treisman, in fact, suggested, that there are two different kinds of searches: parallel searches and serial searches. In parallel searches, the search target pops out from the environment so that you are always able to find it instantly, regardless of how many distracting objects are in the scene. In contrast, if the search target does not pop out, as is the case in serial searches, you have to individually scan each object in the scene to know whether it is your target object or not. In this case, the more distracting objects comprise the scene, the harder the search is. In both parallel and feature searches, the first initial search is characterized by the attributes of the search target. In our example, it depends on the color and artwork of the book, the title, and the author. However, subsequent searches are additionally driven by its location in space. If you remember that you put your book on the top shelf, this information can guide your efforts to this region and thereby make search more efficient. This process of attending preferably to certain regions of the search space is called *location probability cueing.*

Crucially, preferring the top shelf implies that you can either focus your attention on the top shelf or actively ignore the bottom shelf in order to not get distracted by similar looking books in the bottom shelf. The cognitive mechanisms behind this probability cueing of distractor locations are poorly understood and form the rationale for this thesis. This line of studies, therefore, probed into the cognitive mechanisms underlying location probability cueing effects:

1. Is the effect spatial in nature or bound to characteristics of the to-be-suppressed object? In specific, does the suppression mechanism depend on the feature/dimension relationship between the prominent distractor and the to-be-attended search target?
2. Is the probability cueing effect persistent over time? After training on the first day, will we still see a bias towards the former frequent distractor region after 24 hours, even if the distractor is now evenly distributed?
3. Is this kind of statistical learning reflected in the amplitude of the N2pc, a common EEG/ERP marker for shifts in spatial attention?

Before addressing these questions, the introduction outlines *guided search*, a prominent model of visual search and how attention gets captured by distracting objects in visual search, research on location probability cueing and the rationale of this thesis.

Theory of Visual Search

Theories of visual search (Treisman & Gelade, 1980; Wolfe 1994) typically split search up into two phases. The first sweep of the search scene is described as being pre-attentive. This means, that it is based only on physical stimulus properties and no recruitment of attention is required. A very basic search would be described by a visual scene comprising of several simple objects. The observer has to decide whether there is also a specific target object among the rest of the objects, i.e. the distractors. In basic search displays, the features of the distractors can differ from the target in only one visual dimension, like form, shape or orientation (*single-feature* search). For example, the search target is a diamond while all the distractors are squares. This type of search is considered to be fast because the target is very prominent and pops out among the distractors. It is postulated that it is possible to scan all items in the search scene in *parallel*. In a slightly more complex search, the target differs from the distractors by a conjunction of two or more basic features (*feature-conjunction search*). For example, the distractors are either large squares or small triangles, while the search target is the only large triangle. In this case, the target does not pop out among the distractors and attention is required to guide the search *serially* through the display to find the conjunction of features that define the target. This thesis focuses on the former parallel searches in which the search target pops out from the rest of the objects. In parallel searches, visual stimulus *saliency* plays an important role in where attention is allocated (Wolfe, 1994). Saliency is usually referring to a local feature contrast between the target object and distracting objects (Yantis, 1996). The higher this contrast, the more salient the target object is. Further, an object that uniquely differs from other objects in the scene in one or more feature dimensions (e.g. color, shape, orientation) is called a *feature singleton*, because you can select this object unambiguously based on a single feature (for example a red square among blue and green squares). In visual search, selection of single features based on stimulus saliency is representative of one mechanism underlying visual search behavior generally referred to as *bottom-up* attentional capture. These bottom-up processes are founded on the physical properties of the stimuli in the scene.

In every-day searches, we know what we are looking for. Searches are directed towards a specific goal (like finding our wallet), and this guides our attention and thereby influences search behavior. These influences are generally referred to as *top-down* processes. However, when we actively search for a specific object, it is not uncommon that we get distracted by something unrelated. For example, you are looking for your friend in a crowd of people but suddenly you focus your attention on the stranger in a unicorn costume next to you. This *involuntary attentional capture* is empirically investigated using variants of the additional-singleton paradigm (see Yantis, 1996, 2000, for a discussion): the search display typically consists of one singleton target among several homogenous non-targets while some of the scenes also include a singleton distractor. The scenes are normally constructed in a way that the distractor is more salient than the target. For example, a search display could comprise of several vertically oriented bars as non-targets. Your task is to find the bar that is slightly tilted by 10°. However, your attention might get captured by the horizontally oriented bar, because its local feature contrast is higher compared to the search target (i.e. it is more salient). Such attentional shifts are considered involuntary because they interfere with the task of producing a fast response to the target.

The interference caused by these salient additional-singleton distractors can be reduced in some situations (f.e. Müller, Geyer, Zehetleitner, & Krummenacher, 2009). In the study of Müller and colleagues (2009), observers started with a block of trials that contained a shape-defined target and either no distractor or a distractor always defined by color. The subsequent blocks included varying ratios of distractor to no-distractor trials. The results showed that distractor interference varied depending on both the amount of initial exposure to distractors and the ratio of distractors in the subsequent blocks: they caused higher interference when participants had no prior exposure to distractors and when the ratio of distractors was low (the latter reducing the incentive to engage in distractor suppression). This indicates that observers can acquire some efficient strategy to suppress color-defined distractors when searching for shape-defined targets.

But exactly how this suppression of distractors is implemented in the functional architecture of search guidance remains unclear. In a quite recent study, Liesefeld et al. (2017) used distractor bars that were tilted by 45° and target bars that were tilted by 12°. They found that distractors could not be suppressed in this case as the interference remained maximal over the course of the experiment. Therefore, it seems that when searching for an orientation- (or shape-) defined target, the interference caused by a salient singleton distractor can be effectively reduced when the distractor is color-defined (i.e., when it is a *different-dimension* distractor), but not when it is also orientation- (or shape-) defined (i.e., when it is a *same-dimension* distractor). In fact, this pattern is predicted by the *dimension-weighting account* (*DWA*) developed by Müller and colleagues (e.g., Found & Müller, 1996). In essence, DWA is a variation of the *Guided Search* model (e.g., Wolfe, 1994). It assumes that the allocation of spatial attention to objects in visual search is based on a spatial priority map that is computed pre-attentively in the first sweep of the visual scene (later referred to as *master saliency map)*. On the lowest level of the cognitive hierarchy, the stimulus saliency of all the objects in the scene is coded based on their local feature contrast. This contrast can then be enhanced for features that define the search target or reduced for task-irrelevant features via goal-directed top-down modulation. The feature contrast signals computed this way are then integrated across dimensions on the master saliency map and subsequently drive spatial object selection. At the heart of DWA is the notion that this integration on the master saliency map operates in a dimensionally-weighted fashion. This means that a*ll* signals from specific dimensions may be assigned a greater or a lesser influence on guiding the allocation of attention than *all* signals from other dimensions. Accordingly, on the DWA, the non-spatial visual selection is primarily dimension-based, rather than feature-based, but an element of feature-based selection is still possible.

Location probability cueing

Commonly, we do not only search for objects by their features or local feature contrast. A major asset guiding our endeavors is the location in space. For example, if you are looking for a book, it is plausible that you might find it more likely on the bookshelf than on the floor. A similar logic holds true if you search for the same book repeatedly. Imagine you are reading a complicated book on statistics and you put it back on the shelf after each reading session. After two months, you look for it again. You vaguely remember that you put it on the top right shelf, consequently search in this region first and quickly find it. Stated differently: you find the book fast if it is in the location where you expect it to be and slow when it is in a different location. Geng and Behrman (2002) showed that this is also true for more artificial search settings. They presented participants with four different letters distributed over six fixed locations on the screen. The search target was more likely to appear on one side (80%) than on the other (20%) but the participants were not instructed about this manipulation. Participants responded up to 300 ms faster on trials where the search target appeared in the expected (i.e. more probable) locations compared to the unexpected (i.e. less probable) locations. Their experiment was the first to empirically show that observers can use unequal target location distributions to their advantage. This location probability cueing results in the so-called *probability cueing* effect and was since then shown consistently, also in other paradigms (Geng and Behrmann, 2005; Fecteau et al., 2009; Anderson & Druker, 2010). On top of that, a debate has been started about the mechanism behind this probability cueing effect.

The first explanation attributed the effect to a long-term statistical learning of the uneven distractor distribution (Geng and Behrmann, 2002, 2005; Anderson & Druker, 2010). However, as pointed out by Goschy and colleagues (2014), previous investigations had been contaminated by short-term inter-trial facilitation effects. If a search target appears more likely in one specific location, it is also more likely that it appears at this location twice in a row (inter-trial target repetition). Such target repetitions have been shown to facilitate search (e.g. Maljkovic and Nakayama, 1996; Kumada and Humphreys, 2002; Geyer et al., 2007) but the effects are only applicable on a trial-by-trial basis and do not contribute to overall statistical learning. Goschy and colleagues (2014) were able to show two things: First, after varying the location probability distribution of an additional singleton distractor instead of the target, observers were able to suppress the distractor in the region where it appeared more often (90% of the time), leading to decreased response times compared to the region where it appeared less often (10% of the time). Thus, they showed that the probability cueing effect not only applies to search target but extends to salient, task-irrelevant distractor objects. Second, by systematically manipulating the possibility of inter-trial target and distractor repetitions, they showed that the probability cueing effect was attributable to both short-term inter-trial effects and longer-term statistical learning of the distractor distribution. But how does the distractor get learned and suppressed over time? This thesis focuses on how the visual system learns to shield the interference generated by the salient distractors and how this is implemented in its cognitive architecture of search guidance.

Rationale of this thesis

We know that when we manipulate the distractor distribution in such a way, that the distractor appears much more likely in one region (90%; *frequent region*) compared to the other (10%; *rare region*), response times are much lower when it appears in the region where it appears more often. But the mechanisms underlying this location probability cueing are poorly understood. Generally, there are three possible ways distractor suppression in the frequent distractor region could work.

1. **Global spatial suppression**: Distractors appearing in the frequent region might not be directly suppressed. Rather, the reduced interference (or increased suppression) of those distractors is attributable to a global bias, which inhibits the allocation of attention to the frequent region. Stated differently, saliency signals arising in this region are globally down-regulated. If this is the case, the processing of search targets appearing in this spatially suppressed region should be impaired, too. Importantly, this

impairment should even be evident on trials on which no distractor is present because statistically learned, persistent global suppression of the frequent distractor region would operate on all trials. Additionally, it would be independent of whether the distractor is defined in the same- or different dimension.

2. **Feature-based spatial suppression**: Alternatively, spatial shielding may operate at a level below the master saliency map, where features and feature contrast signals are computed. Distractor suppression could operate on the feature maps, down-modulating the distractor-defining feature directly, with stronger down-modulation applied to the frequent region as compared to the rare region. Suppressing a distractor feature signal in the frequent region (more than in the rare region) would decrease its influence when transferred to the corresponding locations on the master saliency map. The resulting saliency signal is thereby decreased, making the distractor less competitive for the allocation of spatial attention. If such a direct feature-suppression is the general mechanism by which shielding works, it would predict no impairment of processing for search targets in the frequent versus the rare distractor region, whether the distractor is defined in the same or a different dimension to the target (as in both cases, only the distractor feature is suppressed).

3. **Dimension-based spatial suppression**: Or, as assumed by the DWA, spatial shielding could operate on the dimension-specific feature-contrast map, down-regulating the strength of any feature-contrast signals in the dimension in which the distractor is singled out from the non-targets, more so for the frequent as compared to the rare region. According to dimension-based spatial suppression, a dissociation would be expected between conditions with distractors defined in the same versus a different dimension to the target (cf. Müller et al., 2009; Zehetleitner et al., 2012): Impairment of

> target processing in the frequent as compared to the rare distractor region would not be expected when the distractor is defined in a different dimension to the target, in which case any signals from the distractor dimension can be suppressed without impacting signals from the target dimension. But impairment would be expected if the distractor is defined within the same dimension as the target: in this case, because of dimensional coupling, applying dimension-based suppression would impact target as well as distractor signals.

We tested these hypotheses by comparing and contrasting the effects of same-dimension versus different-dimension distractors. We were the first to employ a distractor probability cueing paradigm with both same-dimension distractors and different-dimension distractors to directly compare differences in distractor interference and target location effects. As mentioned above, while the probability cueing effect is attributable to both statistical learning and inter-trial facilitation, this thesis focuses on statistical learning. In the first study, we realized this distinction by recruiting a large sample of 184 participants and then computationally removed all trials related to inter-trial effects. We found decisive differences in the probability cueing effects for distractors defined in the same dimension as the target compared to distractors defined in a different dimension. Based on our conclusion that different cognitive mechanisms are involved in the statistical learning depending on the distractor type, we tested whether the learning is persistent over time and still evident after a 24h waiting period (study 3). At the same time, we looked for common neurophysiological markers of this learned distractor suppression with electroencephalography, more precisely in the event-related potentials N2pc and PD (study 2) and probed for a generalization of the revealed mechanisms in the luminance dimension (study 4).

Region-based shielding of visual search from salient distractors: Target detection is impaired with same- but not different-dimension distractors

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Abstract

Shielding visual search against interference from salient distractors becomes more efficient over time for display regions where distractors appear more frequently, rather than only rarely (Goschy et al., 2014). We hypothesized that the locus of this learnt distractor probability-cueing effect depends on the dimensional relationship of the to-be-inhibited distractor relative to the to-be-attended target. If they are defined in different visual dimensions (e.g., color-defined distractor and orientation-defined target, as in Goschy et al., 2014), distractors may be efficiently suppressed by down-weighting feature contrast signals in the distractor-defining dimension (Zehetleitner et al., 2012), with stronger down-weighting applied to the frequent vs. the rare distractor region. However, given dimensionally coupled feature contrast signal weighting (cf. Müller et al., 1995), this dimension-(down-)weighting strategy would not be effective when the target and the distractors are defined within the same dimension. In this case, suppression may operate differently: by inhibiting the entire frequent distractor region on the search-guiding master saliency map. The downside of inhibition at this level is that, while it reduces distractor interference in the inhibited (frequent distractor) region, it also impairs target processing in that region – even when no distractor is actually present in the display. This predicted *qualitative* difference between same- and different-dimension distractors was confirmed in the present study (with 184 participants) – thus, furthering our understanding of the functional architecture of search guidance, especially regarding the mechanisms involved in shielding search from the interference of distractors that consistently occur in certain display regions.

Keywords: visual search, perceptual learning, attentional capture, location probability cueing, location suppression, dimension weighting

Introduction

When looking for a unique target object within a rich visual scene, there are often other objects that stand out from the background of non-target items and that may capture attention before the target is attended. In such visual *pop-out* search tasks, observers become more efficient, over time, in minimizing the interference generated by such salient but task-irrelevant distractors when these are consistently occurring in certain regions of the search display (Goschy, Bakos, Müller, & Zehetleitner, 2014). However, the mechanisms underlying this learning effect, termed *probability cueing of distractor locations* (Goschy et al., 2014), are poorly understood: Do observers learn to suppress distractors based on their likely location alone? Or does space-based suppression combine with feature- or dimension-based suppression mechanisms in some circumstances? And, when there are no effective means of object-based suppression, does space-based suppression become so strong that it affects processing of the search target (counter the intention) as well as of the distractor? These questions were addressed in the present study. – Before developing these questions and considering in detail how probability cueing of distractor locations may work, we review some key notions concerning the functional architecture underlying the competition of unique, *singleton* target and distractor objects in otherwise homogeneous search arrays.

Modulation of interference in involuntary attentional capture

Attentional capture by task-irrelevant objects is usually investigated using variants of the *additional-singleton paradigm* (Theeuwes, 1992; see Yantis, 1996, 2000, for a discussion). While the search display consists of one (task-relevant) singleton-feature target amongst homogeneous non-targets, some or all displays include an additional (task-irrelevant) singleton-feature distractor. Typically, the additional singleton is more salient than the target – frequently, as in Theeuwes (1992), the target is defined by a unique shape (e.g., a diamond among circles) and the distractor by a unique color (e.g., a red circle among green shapes) – so that, generally, it is highly likely to capture the observer’s attention before the target is selected, thereby prolonging reaction times. Such attentional shifts are considered involuntary because they interfere with the task of producing a speeded response to the target.

This interference of salient additional-singleton distractors can be reduced in some situations (e.g., Gaspelin, Leonhard, & Luck, 2015, 2017; Leber & Egeth, 2006a, 2006b; Müller, Geyer, Zehetleitner, & Krummenacher, 2009). Additionally, Zehetleitner, Goschy, and Müller (2012) showed that the interference reduction does not critically depend on the *search mode* (cf. Bacon & Egeth, 1994) adopted by observers (whether *feature* or *singleton search mode*), but on distractor practice (see also Vatterott & Vecera, 2012, and Gaspelin & Luck, 2017, for the role of practice for reducing distractor interference). This indicates that observers can acquire some efficient strategy to suppress color-defined distractors when searching for a shape- (or orientation-) defined target. But exactly how this exclusion of distractors is implemented in the functional architecture of search guidance remains unclear.

One clue to answering this question is provided by Liesefeld, Liesefeld, Töllner, and Müller (2017). Instead of using a color-defined distractor, both distractor and target were defined by orientation: the (less salient) target was defined by a 12° tilt from the vertical, and the (more salient) distractor by a 45° tilt in the opposite direction to the target. Using these stimuli, Liesefeld et al. (2017) observed massive and persistent distractor interference (of 225 ms) over a lengthy EEG experiment. There was no evidence that observers could reduce the attentional capture by the singleton distractor. Rather, the distractors attracted spatial attention – as evidenced by a distractor N2pc wave, a negative EEG deflection at posterior electrodes contralateral to the distractor. Generally, the N2pc is taken to reflect the allocation of attention to an object in the search display (e.g., Luck & Hillyard, 1994; Eimer, 1996; Woodman & Luck, 1999, 2003; Töllner, Rangelov, & Müller, 2012). Crucially, the distractor N2pc was elicited prior to a shift of attention to the target, as evidenced by a delayed target N2pc. Such a signature pattern of successive distractor- and target-related N2pc waves had never been consistently demonstrated before. A reason for this might be that previous studies focusing on the N2pc typically used shape-defined targets and color-defined distractors, making it easy to selectively up-weight target and/or down-weight distractor signals (Hickey, McDonald, & Theeuwes, 2006; Kiss, Grubert, Petersen, & Eimer, 2012; Jannati, Gaspar, & McDonald, 2013; Burra & Kerzel, 2013; Wykowska & Schubö, 2011; among the exceptions are studies with both target and distractor defined in the color dimension, which will be considered further in the General Discussion).

The role of dimension weighting in involuntary attentional capture.

Thus, it would appear that when searching for an orientation- (or shape-) defined target, the interference caused by a salient singleton distractor can be effectively reduced when the distractor is color-defined (i.e., when it is a *different-dimension* distractor), but not when it is also orientation- (or shape-) defined (i.e., when it is a *same-dimension* distractor). In fact, this pattern is predicted by the *dimension-weighting account* (*DWA*) developed by Müller and colleagues (e.g., Found & Müller, 1996; Müller, Heller, & Ziegler, 1995; Müller, Reimann, & Krummenacher, 2003; Krummenacher, Müller, Zehetleiter, & Geyer, 2009). In essence, DWA is a variation of the *Guided Search* model (e.g., Wolfe, 1994; Wolfe, 2007), which assumes that the allocation of focal attention to items in visual search is based on a pre-attentively computed spatial priority map (henceforth referred to as *master saliency map)*: items achieving the highest overall-saliency are attended with priority. The saliency that items take on on this map depends on their feature contrast to other items in their local surround, within all pertinent feature dimensions (e.g., color and orientation contrast). Additionally, this contrast can be top-down enhanced for features that define the searched-for target and possibly also reduced for task-irrelevant features – where the down-weighting of specific features would correspond to *first-order feature suppression* in the terminology recently introduced by Gaspelin and Luck (*in press*). The feature contrast signals thus computed are then integrated across dimensions on the master saliency map and subsequently drive spatial selection. At the heart of DWA (and the critical difference to the original Guided Search model) is the notion that this integration operates in a dimensionally weighted fashion (in contrast to simple saliency summation models, such as Guided Search, which assume non-weighted integration and to models assuming only feature-specific weighting). *All* feature contrast signals from specific dimensions may be assigned a greater or a lesser influence on guiding the allocation of attention than all feature contrast signals from other dimensions. This down-weighting of all feature contrast signals from one dimension would, in a sense, be similar to second-order feature suppression in Gaspelin and Luck's (in press) terminology (i.e., suppression of a *feature discontinuity* on a specific feature dimension, e.g., a color discontinuity, without affecting feature discontinuities in other dimensions, like shape or orientation). Accordingly, on the DWA, non-spatial visual selection is primarily dimension-based, rather than feature-based, without denying an element of feature-based selection (see General Discussion for further details).

Role of dimension weighting in the probability cueing of distractor locations

The present study was designed to examine whether the functional architecture envisaged by DWA (see above) would also help us understand how the probability cueing of distractor locations is mediated. Besides processes of location-independent attentional selection as discussed above, search performance is greatly influenced by the spatial distribution of targets and distractors in the search array. It is well-established that observers can learn to exploit uneven distributions of target locations in order to facilitate search: targets are detected faster at locations where they appear more frequently (e.g., Anderson & Druker, 2010; Fecteau, Korjoukov, & Roelfsema, 2009; Geng & Behrmann, 2002; 2005), which Geng and

Behrmann (2002) termed a *target location probability cueing effect*. Similarly, observers can learn to exploit the statistical distribution of task-irrelevant distractors to improve performance: over time, they become better at suppressing locations where distractors appear frequently (e.g., Kelley & Yantis, 2009; Leber, Gwinn, Hong, & O'Toole, 2016; Reder, Weber, Shang, & Vanyukov, 2003). Note, though, that the relevant demonstrations were limited to sparse visual displays that contained only a few target and distractor stimuli with a very limited number of possible distractor locations.[1] Goschy et al. (2014) showed that distractor location probability learning does generalize from single, specific locations to entire regions of dense search displays. They presented a slightly tilted gray target bar (i.e., an orientation-singleton) among 36 vertical gray non-target bars. In half of the search arrays, one of the vertical non-targets was red, serving as a highly salient color-defined (i.e., different-dimension) distractor. When present, distractors appeared with 90% probability in one half of the display (frequent distractor region) and with 10% in the other half (rare distractor region). Goschy et al. (2014) found that the distractor captured less attention when it occurred in the frequent as compared to the rare region. This result suggests that (at least with different-dimension distractors) we can exploit uneven spatial distractor distributions to facilitate search performance. However, it remains unclear exactly how this suppression is

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[1] Reder et al. (2003) used a variation of the *negative-priming* paradigm (adapted from Tipper, Brehaut, & Driver, 1990): displays consisted of 1 target and 1 distractor, with 4 possible locations, one of which was most likely to contain a distractor. In Kelley and Yantis (2009), the task-relevant red-green dot pattern consistently appeared in the display center, and a distractor (composed of the same colors) could appear at one of two, equally likely peripheral locations. Leber et al. (2016) used a variation of the *contingent-capture* paradigm (e.g., Folk, Remington, & Johnston, 1992): there were 4 display locations/items (arranged in the form of a square), with the distractor display preceding the target display; distractors (which were singled out from the background stimuli by the same feature as the target: the color red) were most likely to appear at one location, defined by a fixed relationship with the likely target location that was indicated by a central arrow at the start of a trial.

implemented, and whether it works in the same way with same- as with different-dimension distractors.

Rationale of the present study

In principle, there are three possibilities of how spatial shielding from distractor interference may work: spatially selective suppression at (i) the global, master saliency level, (ii) the specific feature level, or (iii) the dimensional level.

Master-map-based suppression. One possibility is that the reduced interference from distractors in the frequent distractor region is due to a global bias against the allocation of spatial attention to this region. In terms of search architecture, this would be implemented at the level of the search-guiding master saliency map of the search array (in Gaspelin & Luck's, *in press*, terminology, this is similar to *global-salience suppression*; note, though, that they take this to refer to suppression being reactively applied to the most salient item on the global saliency map, rather than anticipatory suppression of a whole region). Suppression at this level entails that if the frequent distractor region was inhibited on the master saliency map, the processing of search targets appearing in this spatially suppressed region should be impaired, too. This impairment should even be evident on trials on which no distractor is present, because learned, persistent global suppression of the frequent distractor region would operate on all trials, whether or not a distractor appears. Additionally, it would be independent of whether the distractor is defined in the same or a different dimension to the target.

Feature-based suppression. Alternatively, spatial shielding may operate at a level below the search-guiding master saliency map, where features and feature contrast signals are computed, which are then integrated into the master saliency map. Distractor suppression could operate on the feature map, down-modulating the distractor-defining feature directly (in Goschy et al., 2014: the feature 'red'), with stronger down-modulation applied to the frequent as compared to the rare region.

This is essentially a spatially selective version of first-order feature suppression (cf. Gaspelin & Luck, *in press*). Suppressing distractor feature signals in the frequent distractor region (more than in the rare region) would attenuate their weight when transferred to the corresponding locations on the master saliency map, making them less competitive for the allocation of focal attention. If such a direct feature weighting is the general mechanism by which shielding works, it would predict *no* impairment of processing for targets in the frequent versus the rare distractor region, whether the distractor is defined in the same or a different dimension to the target (as in both cases, only the distractor feature is suppressed).

Dimension-based suppression. Alternatively, as assumed by the DWA, spatial shielding could operate on the dimension-specific feature-contrast map, down-modulating the strength of any feature-contrast signals in the dimension in which the distractor is singled out from the non-targets (in Goschy et al.: the dimension 'color'), more so for the frequent as compared to the rare region. This is essentially a spatially selective version of second-order feature suppression (cf. Gaspelin & Luck, 2017). Accordingly, a dissociation would be expected between conditions with distractors defined in the same versus a different dimension to the target (cf. Müller et al., 2009; Zehetleitner et al., 2012): Impairment of target processing in the frequent as compared to the rare distractor region would *not* be expected when the distractor is defined in a different dimension to the target, in which case any signals from the distractor dimension can be suppressed without impacting signals from the target dimension. But impairment would be expected if the distractor is defined within the same dimension as the target: in this case, because of dimensional coupling, applying dimension-based suppression would impact target as well as distractor signals.[2]

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[2] An alternative strategy to dimension-based suppression (which might be deemed counter-productive, as the target can be detected only on the basis of signals in the single critical dimension) might be to resort to inhibition at the level of the master saliency map. But this would again lower

Based on the DWA, our working hypothesis was as follows: probability cueing (i.e., effectively stronger suppression applied to the frequent as compared to the rare distractor region) operates at the dimension-specific level when distractors are defined in a different dimension to the target – leaving target processing unaffected. But when distractors are defined within the same dimension as the target, space-based shielding operates (if it can operate at all) either at the dimension-specific level or at the level of the master map; both would be associated with a cost (i.e., a cost additive to any distractor-probability-cueing effect) for target processing in the frequent region as compared to the rare region.

We tested this hypothesis by comparing and contrasting the effects of same-dimension and different-dimension distractors. Distractor type was manipulated between subjects (i.e., in separate experiments).[3] Specifically, we examined (i) whether a distractor probability cueing effect would also be observed with same-dimension distractors (rather than only with different-dimension distractors); (ii) whether adaptation to the unequal distractor distribution (i.e., frequent vs. the rare distractor region) would also impact target processing; and (iii) whether any such impact would qualitatively differ between the same- and different-dimension distractor conditions.

In order to isolate pure distractor location probability cueing effects, the data need to be cleaned from short-term inter-trial repetition effects and effects of the distance

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the response of saliency units to the target (as well as the distractor) in the frequent (suppressed) region – in line with global spatial shielding (see above). Accordingly, with same-dimension distractors, a target location effect (slowed responding to targets within the frequent vs. the rare distractor region) would be expected in both cases.

[3] The aim of the study was to examine focal hypotheses regarding the effects of target position (dependent on the type of distractor) in distractor probability cueing. These hypotheses were *not* examined by Goschy et al. (2014), who ignored the factor 'target position'. We combined Goschy et al.'s (2014, Experiment 1) data with newly acquired sets of data to raise experimental power and support generalizability. The only difference in some of these new experiments was the non-target color, which was blue instead of gray. Of note, non-target color made no difference to the results, and even without the Goschy et al. (2014) data, the results are essentially the same.

between the target and the distractor in the search array, both of which can influence visual search and both of which may differ between the frequent and rare distractor regions. How we dealt with both types of potential confounds, and what impact they actually have on search performance is described in detail in the Appendix. Note that eliminating potentially confounding trials is costly in terms of the number of trials, or participants, required. We opted for recruiting a larger sample of participants – while keeping the number of trials manageable and consistent with Experiment 1 of Goschy et al. (2014) – by combining the data from several experiments with, in all important respects, identical design.

Method

Participants

One hundred and eighty-four (122 female, 62 male) right-handed observers, with a median age of 26 (range: 18–65) years, participated in the main experiment of this study. They were recruited from participant panels at Ludwig Maximilian University Munich and Birkbeck College, University of London. All of them reported normal or corrected-to-normal (color) vision and gave prior informed consent. They received 8 € (or the GBP equivalent) per hour in compensation. Note that partial results based on the data of 25 of these participants were already reported in Goschy et al. (2014). One subject had to be removed from analyses for missing data (see Appendix).

Apparatus

The experiment was conducted in a sound-reduced, moderately lit test chamber. The search displays were presented on a CRT monitor at 1024 px × 768 px screen resolution and a refresh rate of 120 Hz. Stimuli were generated using either the Experiment Toolbox (Reutter & Zehetleitner, 2012), with a Psychophysics Toolbox

3.0.9 (Brainard, 1997; Kleiner et al, 2007) extension for MATLAB R2007a (The MathWorks®Inc) or OpenSesame 3.0 (Mathôt, Schreij, & Theeuwes, 2012) using a PsychoPy (Peirce, 2007) backend. The observers issued their responses using a QWERTZ [QUERTY] keyboard by pressing the “y” [“z”] or “m” key with their left- or right-hand index finger, respectively.

Stimuli

The stimulus displays were presented on a black background. They consisted of gray (RGB: 127, 127, 127; CIE [Yxy]: 21.22, 0.32, 0.32; for 112 participants) or light blue (RGB: 0, 140, 209; CIE [Yxy]: 57.3, 0.20, 0.20; for 72 participants) vertical non-target bars (0.25° of visual angle wide, 1.35° high), with their centers equidistantly arranged on three imaginary concentric circles with radii of 2°, 4°, and 6°, comprising of 6, 12, and 18 bars, respectively. A further bar occupied the position in the center of the three circles. In every bar, there was a gap of 0.25° in height, which was randomly located 0.25° from the top or bottom of the bar. The target differed from the non-targets by its unique orientation, randomly assigned on each trial: it was tilted 12° to either the right or the left. Note that 12° tilted targets (amongst vertical nontargets) produce reliable ‘pop-out’, as evidenced by a flat search RT/set size function (with a slope near 0 ms/item) for such targets (Liesefeld, Moran, Usher, Müller & Zehetleitner, 2016), indicative of ‘efficient’ search.

If a singleton distractor was present, one of the non-targets was tilted 90° (horizontal; same-dimension distractor) instead of being vertical; or one of the non-targets was red (RGB: 255, 33, 51; CIE [Yxy]: 56.5, 0.60, 0.32) instead of gray (different-dimension distractor).

Note that the singleton target and (if presented) the singleton distractor could appear only at one of the 12 locations on the intermediate circle (i.e., singleton eccentricity was held constant). The non-target stimuli on the outer and inner circles (together with those on the intermediate circle) essentially served to equate local feature contrast amongst the various singleton positions (e.g., Bravo & Nakayama, 1992; Nothdurft, 1993).

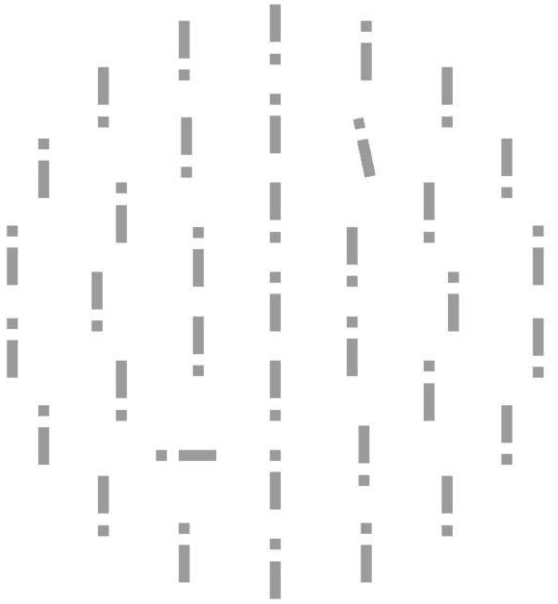

Figure 1. Example of a stimulus display. The search target is the 12°-tilted bar at the 1 o'clock position, and the (same-dimension) distractor is the 90°-tilted bar at the 7 o'clock position.

Design

The type of the singleton distractor (same- and different-dimension) was introduced as a between-subject factor, with 56 observers in the same-dimension condition and 128 in the different-dimension condition (including 25 from Goschy et al., 2014, Experiment 1).

In addition to the type of distractor, the frequency distribution of the singleton distractor across the top and bottom halves of the search displays[4] was manipulated

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[4] In Experiment 1 of Goschy et al. (2014), in addition to the top/bottom manipulation of distractor frequency as described here, there was also a left/right manipulation. Importantly, both 'polarity' manipulations produced comparable patterns of distractor interference effects, that is, there were no

as a between-subject factor, with the top half ranging from the 10 o'clock to the 2 o'clock positions and the bottom half from the 4 o'clock to the 8 o'clock positions on the intermediate circle (see Figure 1). For half of the participants, the top semicircle was the frequent distractor area (10 o'clock to the 2 o'clock positions); for the other half, the bottom semicircle was the frequent distractor area (4 o'clock to the 8 o'clock positions). Neither the distractor nor the target could appear at the 3 o'clock and 9 o'clock positions as these positions could not be unambiguously assigned to the frequent or rare area. A distractor was present in a random 50% of the displays per block. If a distractor was present, it appeared in the frequent area about 90% of the time ('frequent distractors') and in the rare area about 10% of the time ('rare distractors'). The target appeared equally often in both areas, with an equal probability for all 10 possible positions, but it never occurred at the same position as the distractor. The order of the trials within each block was randomized. The experiment consisted of 800 trials in total, subdivided into 8 blocks of 100 trials each.

Procedure

The experimental procedure was identical to that used by Goschy et al. (2014) in their Experiment 1. All observers were instructed in writing and orally that their task was to discern whether the target bar was interrupted (by a gap) at the top or the bottom. If it was interrupted at the bottom, participants had to press the "y" ["z"] key; if it was interrupted at the top, they had to press the "m" key. They were informed that on some trials, there would be a horizontal (same-dimension condition) or, respectively, a red (different-dimension condition) distractor bar which they should simply ignore, as it would be irrelevant to their task. Note that the distractor-defining feature was deliberately fixed, to permit observers to operate

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main or interaction effects involving the factor 'polarity'. Given this, only the top/bottom manipulation was used in further sampling for the present study.

a feature-based suppression strategy (see ‘feature-weighting’ account above). Observers were not informed that the distractor would be more likely to appear in one particular semi-circle.

Each trial started with a white fixation cross in the middle of the screen presented for a random duration between 700 ms and 1100 ms. Then the search display appeared and stayed on until the observer gave a response indicating the gap position in the target bar. If the answer was incorrect, the word “Error” appeared in the center of the screen for 500 ms. Then the next trial started with the onset of the central fixation cross. After each block of trials, observers received RT and accuracy feedback and were free to take a short break before resuming the experiment.

After completing the experiment, participants filled in a brief questionnaire, which was intended to establish whether they had gained any explicit knowledge of the singleton distractors’ spatial frequency distribution (5 response alternatives, i.e.: were distractors equally likely in all display parts or were they more likely in the upper, lower, left, or right display half?).

Analysis

For the RT analyses presented below, we performed no (further) outlier rejection and computed median RT values per participant. We chose Cohen’s *d* to assess effect sizes. Apart from classical frequentist measures, to address issues raised by the ongoing ‘replication crisis’ (cf. Open Science Collaboration, 2015) acknowledged by 90% of scientists (Baker, 2016), we further report for our critical *t* tests (i) 95% highest-posterior-density intervals (HPD) computed with the “coda” package (Plummer et al., 2006) for R (R Core Team, 2014) as the credibility interval, which is a Bayesian parameter estimate (similar to confidence intervals), and (ii) standard JZS prior BF_{10} Bayes factors (Rouder et al., 2009) computed with the BayesFactor package (Morey & Rouder, 2015) for R. BF_{10} gives the relative evidence in the data in favor of H_1, as compared to H_0, that is, the likelihood to which H_1 predicts the observed data better than H_0 (see also Wagenmakers, 2007).

Results

In order to examine for pure statistical learning effects (here: learning of the distractor frequency distribution), potentially confounding effects arising from (i) certain inter-trial transitions as well as (ii) effects attributable to differential target-to-distractor distances between critical conditions, must be eliminated from the data set. Such effects were indeed observed and were subsequently eliminated. They exhibited interesting differential patterns between the same- and different-dimension distractor conditions. Although these effects are tangential to our main findings, we feel that they are of significant methodological importance and theoretical interest. Therefore, we report all analyses in detail in the *Supplementary Results* section and discuss the major findings in the General Discussion.

Analysis of distractor-interference effects

Our main prediction, deriving from the dimension-weighting account, was that the mechanisms underlying the distractor probability-cueing effect (evidenced by reduced interference by distractors in the frequent vs. the rare area) would give rise to impaired target processing only for targets defined within the same dimension as (but not targets defined in a different dimension to) the distractor and only for same-dimension targets located in the frequent (but not targets in the rare) distractor region. To examine for this effect pattern, we first conducted an overall-ANOVA over the whole data set to establish interaction patterns. Based on these, we examined for the existence of the probability-cueing effect for both same- and different-dimension distractors, with a focus on differential target-(position-)related effects between the frequent and rare distractor areas. Finally, for a strong test of differential target-related effects, we directly examined for the predicted pattern on distractor-absent trials, specifically: would target processing be (differentially) impaired in the frequent distractor region even though there is no distractor in the display that could actually cause interference?

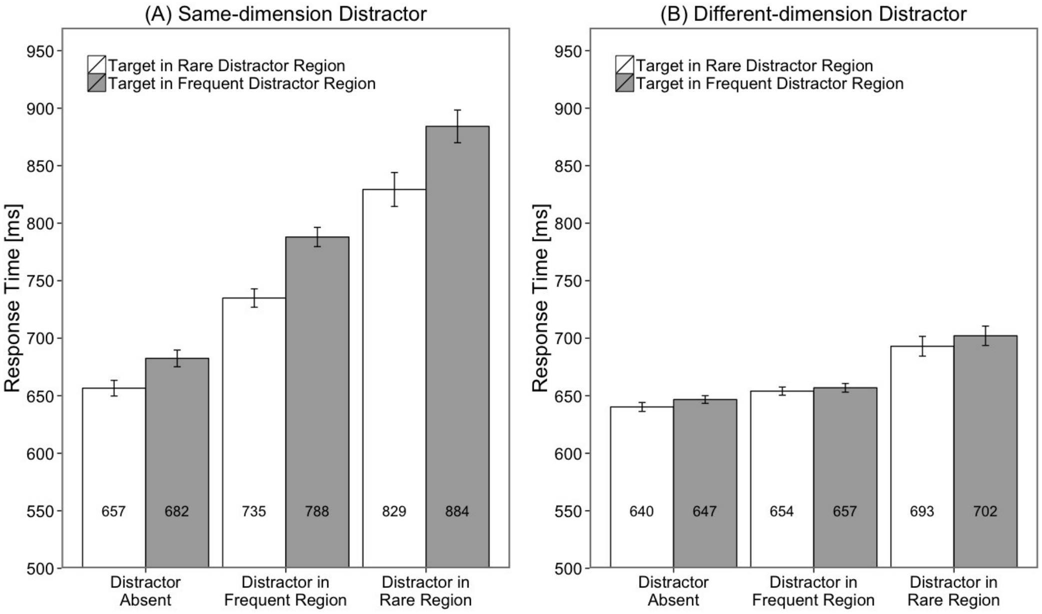

Figure 2. Mean RTs (calculated across participants' median RTs) for targets appearing in the frequent vs. rare distractor region as a function of the distractor condition (absent distractor, distractor in the frequent distractor region, distractor in the rare distractor region) in the same-dimension distractor (horizontal, orientation-defined distractor; panel A) and the different-dimension distractor condition (red, color-defined distractor; panel B). In both conditions, the distractor bar was presented among gray vertical bars and a slightly tilted gray target bar. Error bars depict the within-subject SEM (Morey, 2008).

Participants' median correct RTs[5] (for confound-free trials; see Appendix) were first subjected to an overall (mixed-design) ANOVA with main terms for distractor type (same- vs. different-dimension), distractor location (distractor in frequent area, in rare area, absent), and target location (target in frequent distractor area, in rare

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[5] Note that the error rates (overall error rate: 3.5%) were not influenced by distractor type (same-dimension vs. different-dimension), $F(1,181) = 1.50, p = .222, \eta^2_p = .01$, distractor location (frequent area, rare area, absent), $F(2,362) = 0.135, p = .874, \eta^2_p = .00$, or target location (frequent area, rare area), $F(1,181) = 0.175, p = .677, \eta^2_p = .00$. Also, none of the interactions was significant.

distractor area). This analysis revealed all main effects and two of the three two-way interactions – importantly, both involving the factor distractor type – to be significant[6] (for visualization, see Figure 2). To elucidate the origins of the significant two-way interactions, the same- and different-dimension distractor conditions were examined in two separate (repeated-measures) ANOVAs with the factors distractor condition (distractor in frequent region, in rare region, absent) and target location (target in frequent distractor region, in rare distractor region).

Effects for same-dimension distractors. For same-dimension distractors, the ANOVA revealed both main effects to be significant: distractor location, $F(2,110) = 200.35, p < .001, \eta^2_p = .78$, and target location, $F(1,55) = 13.68, p < .001, \eta^2_p = .20$; the interaction was not significant, $F(2,110) = 1.74, p = .181, \eta^2_p = .03$.

To ascertain that distractors generally caused interference, we directly compared RTs on distractor-present trials with those on distractor-absent trials: RTs were overall slower, by 94 ms, when a distractor was present than when it was absent (761 ms vs. 667 ms; $t(55) = 14.94, p < .001, d_z = 2.00$, 95% HPD [81 ms, 106 ms], $BF_{10} = 8.80 \times 10^{17}$). To directly test for a probability-cueing effect, we contrasted the frequent versus rare distractor-present conditions: RTs were indeed faster, by 87 ms, when a distractor was presented in the frequent area compared to the rare area (761 ms vs. 848 ms), $t(55) = -9.40, p < .001, d_z = 1.26$, 95% HPD [-116 ms, -73 ms], $BF_{10} = 3.27 \times 10^{10}$). Finally, we examined the net distractor-interference effect with reference to distractor-absent trials for the frequent and rare areas separately. Both effects were significant (distractors in rare area: 181 ms; $t(55) = 15.02, p < .001, d_z = 2.01$, 95% HPD [158 ms, 205 ms], $BF_{10} = 1.12 \times 10^{18}$; distractors in frequent area: 84

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[6] Main effects: distractor type, $F(1,181) = 30.34, p < .001, \eta^2_p = .14$; distractor location, $F(2,362) = 220.16, p < .001, \eta^2_p = .55$; and target location, $F(1,181) = 9.62, p = .002, \eta^2_p = .05$. Interactions: distractor type × distractor location, $F(2,362) = 91.71, p < .001, \eta^2_p = .34$; and distractor type × target location, $F(1,181) = 9.38, p = .003, \eta^2_p = .05$. The interactions distractor condition × target location, $F(2,362) = 0.75, p = .471, \eta^2_p = .00$, and distractor type × distractor location × target location, $F(2,362) = 1.53, p = .219, \eta^2_p = .01$, were not significant.

ms; $t(55) = 13.75$, $p < .001$, $d_z = 1.84$, 95% HPD [72 ms, 96 ms], $BF_{10} = 2.59 \times 10^{16}$), with distractors in the rare area causing greater interference than distractors in the frequent area.

Although the distractor condition × target location interaction was not significant – indicative of an additive target-location effect for all three distractor conditions – , the target-location effect was numerically smaller when a distractor was absent in the display (25 ms) compared to when one was present in the frequent or the rare distractor region (53 and 55 ms, respectively). Despite being reduced, the effect on distractor-absent trials was significant: RTs were slower to targets appearing in the frequent versus the rare region (682 ms vs. 657 ms; $t(55) = 3.70$, $p < .001$, $d_z = .49$, 95% HPD [38 ms, 12 ms], $BF_{10} = 51$).

Thus, as expected (on the DWA), there was a significant effect of target location, with slower RTs when the target appeared in the frequent as compared to the rare distractor area. Importantly, this effect was evident even when distractors were absent, that is, when there could not be any distractor interference. This pattern provides strong support for the frequent distractor area being suppressed as a result of distractor (distribution) probability learning, affecting the processing of the target as well as that of the distractor.

Effects for different-dimension distractors. For different-dimension distractors, the ANOVA also revealed a significant main effect for distractor condition ($F(2,252) = 61.64$, $p < .001$, $\eta^2_p = .33$), but (in contrast to same-dimension distractors) not for target location ($F(1,126) = 0.92$, $p = .339$, $\eta^2_p = .01$); the interaction was also not significant ($F(2,252) = 0.19$, $p < .827$, $\eta^2_p = .00$).

Distractors again caused general interference (main effect of distractor condition): RTs were slightly, but significantly, slower overall on distractor-present compared to distractor-absent trials (656 ms vs. 642 ms; $t(126) = 6.73$, $p < .001$, $d_z = 0.60$, 95% HPD [10 ms, 18 ms], $BF_{10} = 1.76 \times 10^7$); note that this interference effect was much smaller compared to that with same-dimension distractors (14 ms vs. 94 ms). Furthermore, a comparison of the frequent versus the rare distractor-present condition revealed RTs to be indeed faster when a distractor was presented in the frequent area compared to the rare area (654 ms vs. 689 ms), $t(126) = -6.10, p < .001$, $d_z = 0.54$, 95% HPD [-46 ms, -23 ms], $BF_{10} = 1.73 \times 10^6$), though this probability-cueing effect, too, was much smaller compared to that with same-dimension distractors (35 ms vs. 87 ms). Finally, as expected, the net distractor interference effect with reference to distractor-absent trials was greater for distractors in the rare area (47 ms; $t(126) = 7.74, p < .001, d_z = 0.69$, 95% HPD [34 ms, 59 ms], $BF_{10} = 2.79 \times 10^9$) than for distractors in the frequent area (11 ms; $t(127) = 5.93, p < .001, d_z = 0.53$, 95% HPD [7 ms, 15 ms], $BF_{10} = 4.05 \times 10^5$); these net effects of 47 ms (rare area) and 11 ms (frequent area) compare with 181 ms and, respectively, 84 ms for same-dimension distractors.

Concerning the (non-significant) target-location effect, RTs were overall only slightly slower to targets in the frequent versus targets in the rare distractor area. This effect was non-significant for all three distractor conditions (distractor absent: 647 vs. 640 ms; $t(126) = 1.43, p = .154, d_z = 0.13$, 95% HPD [15 ms, -2 ms], $BF_{10} = 0.27$; distractor in frequent area: 657 ms vs. 654 ms; $t(126) = 0.56, p = .580, d_z = 0.04$, 95% HPD [12 ms, -8 ms], $BF_{10} = 0.11$); distractor in rare area: 702 ms vs. 693 ms; $t(126) = -0.69, p = .493, d_z = 0.06$, 95% HPD [34 ms, -17 ms], $BF_{10} = 0.12$).

Distractor-absent trials. Arguably, the strongest evidence for learned, persistent spatial suppression on the master saliency map, or the lack of it, would derived from the distractor-absent trials, for which spatial suppression of target processing can be assessed in its pure form, without any effect of a competing distractor. Thus, to examine for differential suppression patterns between same- and different-dimension distractors, we directly compared and contrasted the effects of the two distractor types in the distractor-absent condition in a distractor type × target location (mixed-design) ANOVA. This analysis revealed a significant main effect for target position (F(1,181) = 10.71, p = .001, η^2_p = .06), whereas the main effect of distractor type was non-significant (F(1,181) = 3.11, p = .079, η^2_p = .01). Importantly, the effect of target location was significantly modulated by the distractor type (F(1,181) = 5.58, p = .019, η^2_p = .03). Given this interaction, we compared the target-location effects (i.e., the mean differences between the two target-location conditions) between same- and different-dimension distractors. The results were in line with our hypothesis: the target-location effect (the disadvantage for targets appearing in the frequent vs. the rare area) was significantly larger with same-dimension (26 ms) than with different-dimension distractors (6 ms): t(181) = 2.36, p = .019, d = 0.38, 95% HPD [8 ms, 24 ms], BF_{10} = 4.4. Additionally, the target-location effect differed significantly from 0 for same-dimension distractors (t(55) = 3.70, p < .001, d_z = .49, 95% HPD [11 ms, 39 ms], BF_{10} = 51), but not for different-dimension distractors (t(126) = 1.43, p = .154, d_z = 0.13, 95% HPD [-2 ms, 15 ms], BF_{10} = 0.27).

Post-experiment questionnaires

We also examined whether the interference reduction for the frequent versus the rare distractor area depended on participants having ‘recognized’ the frequency distribution. If so, this would imply that the suppression of distractors in the frequent area might have relied on a conscious effort. In the post-experimental questionnaire, 43 out of the 183 (23%) participants indicated the distractor frequency distribution correctly. While this would be chance level (recall that there were five response alternatives, so chance level would be 20%), it should be noted, however, that the majority of participants (53%) opted for the response ‘equal distribution’, rather than committing to a specific region in which distractors were (believed to be) likely.[7] When committing to a specific response, the correct

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[7] Note that the response alternative ‘equal distribution’ was introduced to exactly follow the awareness-test procedure of Goschy et al. (2014).

distractor region was significantly more likely to be chosen than any of the three alternatives (55% vs. 45% [= 3 × 15%]; $\chi^2(1) = 30.73, p < .001$) – indicative of a degree of awareness of the actual distractor distribution. Importantly, the degree of 'awareness' was little influenced by the distractor type: 20% and 25% correct answers (given 5 response alternatives, including the 'equal-distribution' option) with same- and different-dimension distractors, respectively. Of those who committed to a specific response, 48% (same-dimension distractors, $\chi^2(1) = 4.15, p = .042$) and 57% (different-dimension distractors; $\chi^2(1) = 23.76, p < .001$) answered correctly.

Comparing participants who answered correctly with those who responded incorrectly (including those who gave an 'equal-distribution' answer) in an awareness (correct/incorrect answer) × distractor type (same-/different-dimension) × distractor location (frequent/rare area) ANOVA of the median RTs revealed no two-way interactions involving awareness (awareness × distractor type, $F(1, 179) = 1.75, p = .188, \eta^2_p = .01$; awareness × distractor location, $F(1, 179) = 3.21, p = .075, \eta^2_p = .02$), but the three-way interaction was significant, $F(1, 179) = 7.56, p = .007, \eta^2_p = .04$. Follow-up ANOVAs, with the factors awareness and distractor location, calculated separately for each distractor-type condition, failed to reveal significant main effects of awareness for both different-dimension and same-dimension distractors (different-dimension distractors, $F(1, 125) = 0.03, p = .858, \eta^2_p = .00$; same-dimension distractors, $F(1, 54) = 2.65, p = .110, \eta^2_p = .05$). However, for same-dimension distractors (but not different-dimension distractors, $F(1, 125) = 0.01, p = .915, \eta^2_p = .00$), the awareness × distractor location interaction was significant: $F(1, 54) = 9.49, p = .003, \eta^2_p = .15$, reflecting the fact that (the 11) 'aware' participants showed a larger probability-cueing effect than (the 45) 'non-aware' participants (158 ms vs 83 ms; $t(54) = 3.08, p = .003, d_z = 1.04$, 95% HPD [91 ms, 141 ms], $BF_{10} = 12$). Given that the overall RT speed was comparable between the 'aware' and 'non-aware' groups (774 ms vs 745 ms; $t(54) = 0.77, p = .443, d_z = 0.26$, 95% HPD [720 ms, 793 ms], $BF_{10} = 0.408$), the larger probability-cueing effect for the ‘aware’ participants provides an indication that, with same-dimension (but not with different-dimension) distractors, the probability-cueing effect may be (strategically) enhanced as a result of observers explicitly recognizing the display half in which the distractor was more or, respectively, less likely to appear.

Discussion

The present study revealed a paramount difference in the probability-cueing effect between same- (orientation-) and different- (color-) dimension distractors in visual singleton search. While both distractor-type groups showed significant learning of the spatial distractor distribution (as evidenced by reduced interference from distractors that appeared in the frequent, as compared to the rare, distractor area), the interference was higher overall – by a factor of at least 4 – with same- relative to different-dimension distractors. In addition, there was a qualitative difference in the interference pattern caused by same- versus different-dimension distractors. Search under conditions of same-dimension distractors was associated with a target-location effect (i.e., slowed responding to targets appearing in the frequent vs. the rare distractor region). This was observed even for displays that did not contain a distractor. No target-location effect was evident in search under conditions of different-dimension distractors. We will discuss the implications of these effects in turn, while also touching upon the issue of the nature – implicit versus explicit – of distractor probability learning.

Same-dimension distractors cause greater interference than different-dimension distractors

The differential magnitude of interference between same- and different dimension distractors is in line with previous reports that distractors that are similar to the search target cause more interference to begin with (e.g., *DWA*: Müller et al., 2009; Zehetleitner et al., 2012; *ambiguity account*: Olivers & Meeter, 2006; Meeter & Olivers, 2006; Pashler, 1987)[8]. Additionally, the present data show that shielding from the interference generated by distractors frequently occurring in a particular display area *cannot* be learned as effectively with target-similar as with target-dissimilar distractors: same-dimension distractors continued to produce strong interference even in the frequent distractor area, which compares with weak interference by frequent-area distractors in the different-dimension condition.

This effect pattern argues against feature-based accounts, according to which distractor suppression is achieved by the independent down-weighting of distractor features (first-order order feature suppression) and/or up-weighting of target features. In theory (cf. Wolfe, Friedman-Hill, Stewart, & O'Connell, 1992; Wolfe & Horowitz, 2017), independent weighting of (target) features should work effectively as long as the features are clearly separable. In the present study, this was the case not only in the different-dimension condition, but also in the same-dimension condition: the distractor was consistently rotated by 90° from the vertical as compared to a variable (left or right) target tilt of 12°. According to Wolfe et al. (1992), this is a 'categorical' feature difference capable of guiding search. Apparently, however, this categorical difference could not be exploited by

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[8] While this pattern can be described in *similarity* (or *ambiguity*) terms, we propose it reflects fundamental, dimension-based constraints in the functional architecture of search guidance. Further research is necessary to discriminate between the essentially continuous similarity (or ambiguity) vs. discrete dimension-based accounts.

participants in the same-dimension distractor condition, effectively ruling out a strict, feature-based account (at least for the orientation dimension).

Instead, a straightforward, mechanistic account of the differential interference between same- and different-dimension distractors effects is provided by the DWA: due to the (assumed) hierarchical organization of saliency computation and dimensionally coupled weighting of feature-contrast signals (e.g., Zehetleitner et al., 2012), it is harder to suppress known distractors defined by features in the same dimension as the target, compared to features in a different dimension. As will be detailed below, DWA readily explains why distractor interference is greatly increased overall in the same-, as compared to the different-, dimension condition (94 vs. 14 ms). Interference effects approaching 100 ms suggest that attention was actually captured by the distractor on a large majority of trials (consistent with Liesefeld, Liesefeld, et al., 2017, who also used orientation-defined distractors and targets).

Differential mechanisms underlie the probability-cueing effects in same- versus different-dimension distractors

The differential pattern of distractor location probability-cueing effects – specifically, the differential target location effects between the same- and different-dimension conditions –cannot be explained by spatially selective versions of either feature-based (or first-order feature) suppression models or master-map-based suppression models. Master-map-based suppression would predict *impaired* processing of targets in the frequent distractor region, regardless of whether the distractor is defined in the same or a different dimension to the target. Feature-based suppression models would always predict *unimpaired* processing of targets in the frequent distractor region, regardless of whether distractors are defined in the same or a different dimension to the target. The fact that target processing in the frequent region was slowed only in the same-, but not in the different-, dimension distractor condition effectively rules out that either of these mechanisms can account for the present set of findings on its own.

But this pattern is consistent with the DWA, according to which the distractor-defining dimension can be suppressed as a whole, with greater suppression applied to the frequent than to the rare distractor area. However, dimension-based (or second-order feature) suppression would leave target processing unaffected only when the distractor is defined in a different dimension to the target. By contrast, when the distractor is defined in the same dimension as the target, two strategies of reducing distractor interference would be available: dimension-based suppression or master-map-based suppression, in both cases with stronger suppression assigned to the frequent than to the rare distractor region – that, however, would both impair target processing. With both strategies, the power of distractors appearing in the frequent area to capture attention would be reduced, compared to distractors in the rare area, giving rise to probability-cueing effects. But the downside would be that targets falling in the frequent (i.e., suppressed) region are responded to *slower* than targets in the rare region. Both these effects were evidenced by the data, consistent with either of the two strategies.

With same-dimension distractors, dimension-based suppression would appear to be a less plausible strategy than master-map-based suppression, as any down-weighting of the orientation dimension would conflict with the task of finding the orientation-defined target.[9] However, no such conflict would arise if the down-modulation is applied to the (spatial) master saliency map. This representation is

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[9] To solve the task, observers would have to actively maintain a template of the orientation target in visual working memory, to decide whether a stimulus that summons attention is a target (rather than a distractor), as well as to top-down bias search towards stimuli matching the target description (e.g., Soto, Hodsoll, Rotshtein, & Humphreys, 2008; Olivers, Peters, Houtkamp, & Roelfsema, 2011). There would thus be a goal conflict with observers, at the same time, attempting to keep any signals from the orientation dimension out of the search and selectively enhancing the target orientation.

assumed to be feature- and dimension-less. Master map activations as such convey no information as to how, by which feature and in which dimension, they were produced. Rather, post-selective back-tracking to lower, dimension- and feature-coding, levels may be required to extract this information (e.g., Töllner , Rangelov, & Müller, 2012). Given this, applying spatial inhibition at this level would conflict less with the goal of finding and responding to an orientation-defined target. Additionally, the target-location effect was even evident on distractor-absent trials, strongly supporting spatially selective master-map-based suppression.

With different-dimension distractors, distractor interference can be rather effectively reduced by dimension-based suppression – as a result of which feature-contrast signals from this dimension arrive attenuated at the saliency summation stage (the master map), reducing their power to capture attention. Importantly, to explain the probability-cueing effect (35 ms faster RTs to targets in the frequent vs. the rare area), one would have to additionally assume that, as a result of probability learning, the dimension-based down-modulation of feature-contrast signals from the distractor dimension becomes stronger for the frequent than for the rare distractor area. Stronger down-modulation of feature contrast signals from the distractor dimension within the frequent area would leave target signals from another dimension unaffected. Consistent with this, RTs were *not* significantly slower to targets in the frequent area than to targets in the rare area.

Of note, this qualitative difference between the two distractor-type conditions is even seen in a comparison of the *distractor-absent* trials, on which cannot be any 'confounding' by a competing additional singleton in the display: here, there was no reliable target location effect with different-dimension distractors, but a significant (26-ms) effect with same-dimension distractors – despite generally similar RT levels on distractor-absent trials (on which the displays were identical for the two groups).

Implications for the cognitive architecture underlying distractor probability cueing

These results have implications for drawing conclusions about the cognitive architecture mediating the distractor probability (distribution) learning effects (see Figure 3): Suppression of *different-dimension* distractors operates at a level below the master saliency map (Figure 3A). Interfering feature-contrast signals from the distractor-defining dimension are down-modulated, so that their contribution to overall-saliency signaling is effectively reduced, yielding lower distractor interference overall; at the same time, feature-contrast signals from the target dimension are left unaffected. By contrast, *same-dimension* distractors generate a comparatively large interference effect, and RTs are significantly slowed when the target appears in the frequent as compared to the rare distractor area – even when no distractor (that could cause interference) is actually present in the display. The latter effect is readily explained by assuming that the frequent distractor region is suppressed either at the super-ordinate level of the master saliency map (Figure 1B; our preferred account), or, alternatively, at the level of the orientation-dimension map, which in both cases would affect target as well as distractor signals.

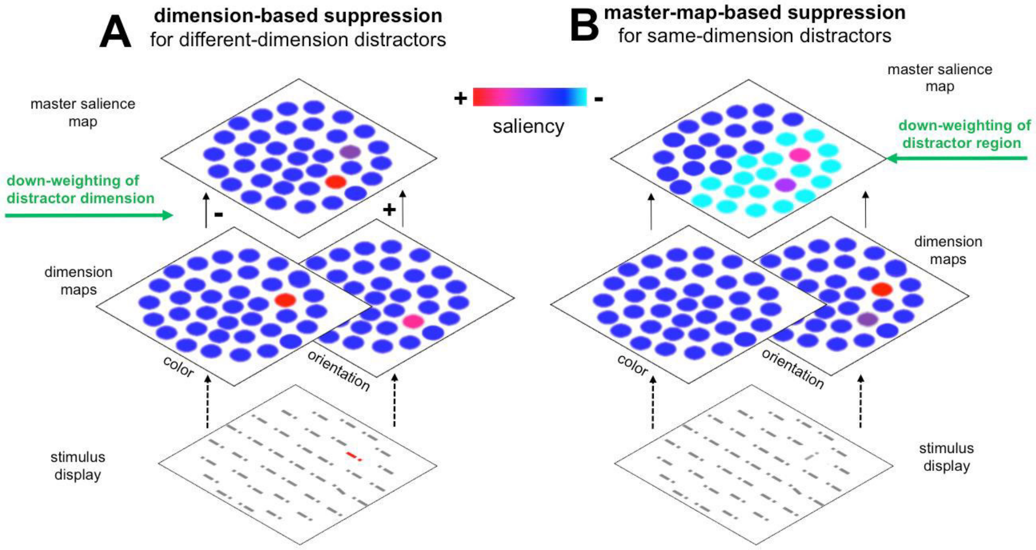

Figure 3. Schematic representations of the two suppression models involved in the probability cueing of distractor locations, which are supported by the data: (A) dimension-based suppression for different-dimension distractors and (B) master-map-based suppression for same-dimension distractors. The search display depicted at the bottom of each panel contains an orientation-defined target (12° tilted relative to vertical non-targets) and (A) a color-defined (red bar) and (B) an orientation-defined (horizontal bar) distractor. The map in the middle of each figure represents the dimension map at which feature contrast signals are combined for separable feature dimensions (in the example, color and orientation). The map depicted at the top of each figure is the search-guiding 'master salience map'. In all maps, hotter colors depict higher and cooler colors lower saliencies. (A) In dimension-based suppression, the weighting of target and distractor signals occurs at the level of the dimension maps; i.e., feature weighting is dimensionally coupled, so that distractor signals can be down-weighted without affecting target signals only when target and distractor are defined in different dimensions. Note that, in (A), the combined feature contrast signals from the color dimension are negatively weighted on their transfer to the master salience map, reducing their impact on overall-saliency coding. Distractor probability cueing could be explained by greater down-weighting of signals from the distractor-defining dimension for the frequent (lower display half) compared to the rare distractor region (upper half); note that this differential down-weighting is not depicted in the figure. (B) For same-dimension distractors, distractor probability cueing could operate by spatially selective suppression of a whole region of the search display (in the example, the lower half) operating at the level of master salience map. – With both mechanisms depicted, interference would be reduced for distractors appearing in the frequent as compared to the rare distractor region. See text for further explanations.

However, while the present findings are in line with the DWA (the only general account predicting a dissociation between same- and different-dimension distract!), further work – for instance, with luminance-, color-, and motion-defined targets (and distractors defined in either the same or one of the other dimensions) – is necessary for the DWA to be established as a truly general account of the asymmetry revealed in the present study. Of note, there is evidence that, within the color dimension, salient singletons mismatching the target color (i.e., same-dimension distractors) may fail to capture attention. This has been demonstrated in contingent-capture studies, with temporally separated presentation of the singleton distractor and target displays (Folk, Leber, & Egeth, 2002; Lien, Ruthruff, & Cornett, 2010; Lien, Ruthruff, & Johnston, 2010), and in additional-singleton studies, with target and distractor in the same display (e.g., Gaspar & McDonald, 2014; Gaspar, Christie, Prime, Jolicoeur, & McDonald, 2016). In additional-singleton studies, non-matching colors usually interfered relatively little[10], though there are exceptions; for instance, Kandel, Feldmann-Wüstefeld, and Schubö (2017) observed that, once participants had learned that green and blue singletons were response-relevant in a categorization task (green-vs.-blue response), they showed substantial interference, of 37 ms, by a red (i.e., non-target-colored) additional-singleton distractor in a compound-search task, along with ERP indices of attentional capture (see also Feldmann-Wüstefeld, Uengoer, & Schubö, 2015). Similarly, in the contingent-capture literature, while mis-matching colors usually produced relatively little interference, a more recent study revealed that with a target that could be either red or green, distractors in a non-target color (blue) led to a comparably-sized capture effect to target-colored distractors (whereas motion-defined distractors failed to capture attention; Harris, Becker, & Remington, 2015). Despite these exceptions (which are consistent with dimension-based attentional settings), on the balance of evidence, it would appear that the suppression of color distractors does involve an element of feature-based suppression (see also Gaspelin, Leonard, & Luck, 2015, and Gaspelin & Luck, 2017, for evidence of first-order, as opposed to second-order, color feature suppression in a paradigm with shape targets and color distractors, where the distractor color was either constant/predictable [Gaspelin et al., 2015] or variable/non-predictable [Gaspelin & Luck, 2017] across trials). This picture is actually consistent with previous studies of dimension weighting (with combinations of color, motion, and orientation targets), in which color proved to be special: it was the only dimension producing

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[10] For instance, in Gaspar & McDonald (2014, Experiment 1: yellow target, red distractor, presented amongst green non-targets), the color distractor generated significant interference of 18 ms; while it produced no N2pc (which would have been indicative of attentional capture), it elicited a P_D (i.e., with a midline target, the ERP waveform was more positive contralateral vs. ipsilateral to the distractor 250–300 ms post display onset), which is thought to reflect – in this case: feature-based – distractor suppression (e.g., Hickey, Di Lollo, & McDonald, 2009; Sawaki, Geng, & Luck, 2012). Note though that a significant P_D was evident only on fast-response trials, but not on slow-response trials, suggesting failure of distractor suppression on some proportion of (slow-response) trials.

significant feature-specific inter-trial priming and trial-wise pre-cueing effects[11] (e.g., Found & Müller, 1996; Müller et al., 2003; Weidner, Pollmann, Müller, & von Cramon, 2002) – underscoring the dictum that 'not all features or dimensions were created alike' (e.g., Nothdurft, 1993; Wolfe, Chun, & Friedman-Hill, 1995). Accordingly, feature-based distractor suppression may be possible, to some extent, with color distractors (which produce relatively small intra-dimensional interference effects; e.g., Gaspar & McDonald, 2014; Gaspar et al., 2016), while it does not appear to be possible with orientation distractors (which produce large intra-dimensional interference effects; e.g., Liesefeld, Liesefeld, et al., 2017, and present study). Nevertheless, given the available evidence from dimension-weighting studies, we would predict dimension-based effects to outweigh feature-based effects even with color distractors. Purpose-designed studies, with carefully calibrated color and orientation stimuli, as well as generalization to other combinations of singleton (target and distractor) dimensions involving luminance, color, and motion stimuli, would be necessary to examine this prediction. This is beyond the scope of the present study.

Assuming reasonable generalizability, note that the search architecture envisaged by DWA does not exclude feature-based selection – which is, after all, assumed to be the prime principle of non-spatial selection in virtually all models of visual search

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[11] For instance, Found & Müller (1996) found that, in color/orientation pop-out search, repetition of the precise target color feature across trials (e.g., red → red) conferred an advantage over a color switch (e.g., blue → red), with the latter yielding an advantage compared to a dimension switch (e.g., right-tilted → red). With orientation-defined targets, by contrast, only a dimension-specific switch effect was seen. Similarly, Müller et al. (2003) found that when a particular target color was precued to be likely at the start of a trial (e.g., red, cue validity $p=.79$), there was a significant advantage for targets singled out by this feature compared to targets defined by another color feature (e.g., blue, $p=.07$) or by an orientation feature (45° left- or right-tilt, each $p=.07$). Of note, there was also some advantage for targets defined by the non-cued color feature (i.e., blue when the cue indicated red; same-dimension feature) compared to the two orientation features (different-dimension features) even though all non-cued features were equally unlikely. For orientation-defined targets, by contrast, there was no significant feature-specific cueing effect, i.e., no graded advantage for the cued vs. the non-cued orientation feature. These results point to a greater role of feature-specific coding for the color dimension compared to the orientation dimension.

and selective attention (*Guided Search*, e.g., Wolfe, 2007; *template-based guidance*, e.g., Duncan & Humphreys, 1992). DWA only claims that for features defined within the same dimension, one cannot independently modulate one feature-contrast signal (e.g., the target signal) from another (e.g., the distractor signal) as regards their cross-dimensional *integration/summation weights* by units of the master saliency map. While some theorists have criticized DWA for being unable to account for findings of feature selectivity, one straightforward extension would be to assume a combination of independent intra- and cross-dimensional weights: intra-dimensional weights would ensure that one can, to some extent, up-modulate the target feature and/or down-modulate the distractor feature in the computation of dimension-specific (i.e., within-dimensions) feature contrast signals (as assumed by, e.g., Guided Search). However, both these (feature-weighted) signals would then be multiplied by the same dimensional weight on being transferred to the master saliency map. Such a scheme would ensure an element of feature selectivity, while also maintaining the principle of dimensional weight coupling – which is at the heart of DWA!

Distractor probability cueing: explicit or implicit in nature?

In previous studies of distractor location probability cueing (Goschy et al., 2014; Leber et al., 2016), participants were typically unable, at the end of a lengthy experiment, to tell at above-chance level at which locations distractors were likely to appear. This was taken to suggest that the distractor probability cueing effect is essentially implicit in nature (Reder et al., 2003, too, assume that their *negative location priming* effect operates outside conscious awareness, though without having examined for this). However, all these studies employed only relatively small numbers observers (e.g., 19 participants in Goschy et al., 2014; 26 participants in Leber et al., 2016), making it hard to actually establish above-chance recognition of the likely distractor locations. Given our large sample, we had reasonable power to determine whether participants could tell above chance in which display region a distractor was most likely to appear. While responses appeared to be at chance when looking at the proportion of participants who correctly selected the frequent distractor region (out of the total number of observers), a more detailed analysis revealed significant above-chance performance among those participants who did not chose a non-committal, ‘equal-distribution’ response. This was the case whether participants had performed the task under the different- or the same-dimension distractor condition. As same-dimension distractors caused massive interference, one could have surmised that a majority of observers might have become aware of the unequal distribution – which was, however, not borne out by the data.

Partitioning the participants into two ‘awareness’ groups (‘aware’ = correct answer, ‘unaware’ = incorrect answer) and re-examining the probability-cueing effect as a function of group revealed no significant main effect of ‘awareness’. However, there was an interaction of ‘awareness’ with distractor condition for the same-dimension group, with ‘aware’ participants exhibiting a larger probability-cueing effect (157 ms, which compares with 83 ms, that is, half the effect, for the ‘non-aware’ group), without responding significantly slower. This would argue that (perhaps the majority of) these 11 observers became genuinely aware of the distractor frequency distribution, which made them increase the inhibition they applied to the frequent distractor area. Of note this would predict that aware participants also exhibit an enlarged target position effect – which is, at least numerically, borne out by the data. Note, however, that above chance performance does not necessarily imply awareness, and further studies are necessary to resolve this question (ideally excluding the ‘equal- distribution’ response and including confidence ratings).

Thus, our data provide some indication (at variance with Goschy et al., 2014, who had only a small sample of participants compared to that analyzed in the present study and who examined only correct versus all incorrect, including ‘equal-distribution', responses) that distractor probability cueing might reflect, at least to some extent, an explicit learning effect. This would place distractor probability cueing with other, perceptual-learning effects in the search literature, notably *contextual cueing* – an effect that is similarly associated with a (limited) degree of explicit awareness of repeatedly encountered target-nontarget configurations (Smyth & Shanks, 2008, and Vadillo, Konstantinidis & Shanks, 2015; though see Chun & Jiang, 2003; Colagiuri & Livesey, 2016; Goujon & Thorpe, 2015). Note, though, that whether conscious awareness drives distractor probability cueing is another matter: conceivably, the effect may be implicitly driven, while being associated with (a degree of) explicit awareness (see Geyer, Müller, Assumpcao, & Gais, 2013, with regard to contextual cueing). However, with same-dimension distractors – which require enhanced cognitive control to deal with capture events – observers who became consciously aware of the distractor distribution appeared to adjust the strength of spatial suppression accordingly. No such adaptation was evident with different-dimension distractors, presumably because these require a lesser degree of cognitive control to be filtered out effectively.

Location-specific inter-trial and lateral-inhibition effects

The supplementary analyses (see Appendix for details) revealed significant modulations of RTs by positional inter-trial effects, in particular, expedited RTs when the current (trial *n*) target appeared at the location of the previous (trial *n-1*) target (T_{n-1}–T_n transition) – in line with the *positional*-priming literature in visual search (e.g., Maljkovic & Nakayama, 1996; Kumada & Humphreys, 2002; Geyer, Müller, & Krummenacher, 2007). This is interesting because we used relatively dense displays (with 36 items), whereas hitherto positional inter-trial effects have been investigated and reported mainly with relatively sparse displays (as with the *priming of pop-out* paradigm, where displays typically consist only of three relatively widely spaced items). On the other hand, positional inter-trial priming effects have been reported by Krummenacher et al. (2009) for both singleton detection and compound-search tasks (both with dense displays): RTs were expedited to targets on trial n that appeared at (roughly) the same position as the target on trial n-1, and this effect was more marked for compound-search than for simple detection tasks, even though the target singleton was exactly the same in both cases. Related to distractor probability cueing, Goschy et al. (2014) had found evidence that, to some extent, the interference reduction for the frequent (as compared to the rare) distractor area was due to positional inter-trial effects, in particular: interference was reduced when the distractor on the current trial occurred at the same location as the previous distractor (D_{n-1}–T_n transition) – a finding confirmed in the present study. Additionally, the present, more comprehensive inter-trial analysis showed that if a target appears at the same location as the last distractor (D_{n-1}–T_n transition) or if a distractor occurs at the same location as the last target (T_{n-1}–D_n transition), RTs are slowed. Given that such repetition effects were much more likely to happen in the frequent as compared to the rare distractor area, they would have affected both areas differentially and thereby confounded the results. This highlights the necessity to control for positional inter-trial effects when examining effects of distractor location probability cueing.

Theoretically of potential importance, the inter-trial transition effects – that is, both the (inter-trial) distractor-location inhibition (D_{n-1}–T_n trials: 53 ms vs. 13 ms; D_{n-1}–D_n trials: -32 ms vs. -2 ms), and to some extent also the target-location facilitation (at least on T_{n-1}–T_n trials: -70 ms vs. -49 ms) – were greatly increased in the same-, relative to the different-dimension, condition (distractor-location inhibition was increased by a factor of at least 4!).

In addition to positional inter-trial effects, the supplementary analyses revealed significant intra-trial modulations of RTs by the spatial distance of the target relative to the distractor. It is thought that when a salient distractor captures attention, it must be (actively) suppressed for focal attention to move on to the next most salient item, the target (see, e.g., Liesefeld, Liesefeld, et al., 2017), and this suppression affects not only the distractor location itself, but spreads laterally to the surrounding region, tailing off gradually with increasing distance from the distractor location (e.g., Gaspar & McDonald, 2014; Mathot, Hickey, & Theeuwes, 2010; Mounts, 2000).[12]

Importantly, in the present study, this intra-trial lateral inhibition effect centered on the distractor position was also greatly increased, by a factor of three, for same-dimension compared to different-dimension distractors (measured in terms of the rate of RT decrease as a function of the distance of the target from the distractor: -12.99 ms vs. -4.72 ms per degree of visual angle). This pattern mirrors the increased cross-trial distractor location inhibition with same- as compared to different-dimension distractors, suggesting that it is the inhibition brought to bear on the distractor on a given (distractor-present) trial that is then carried over into the next trial.

Overall, this pattern is consistent with the idea that the harder the search and, particularly, the harder it is to shield from distractor interference, the greater the positional intra- and inter-trial effect. Concerning the intra-trial inhibition (and the cross-trial carry-over of inhibition) of the distractor location, the more likely it is that the distractor captures attention, the greater the suppression applied. There may be two explanations for this: One is that, on a given trial, the amount of inhibition placed on the distractor location is increased in the different-, compared to the same-, dimension distractor condition. Alternatively, the amount of inhibition is the same on a single-trial basis, but given that same-dimension

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[12] Attentional capture by the distractor may not actually be necessary for target-to-distractor distance effects to manifest. For instance, Gaspar and McDonald (2014) observed a behavioral distance effect (of maximally 55 ms) even though, in their event-related analysis of the EEG, they found no N2pc to the distractor.

distractors generate capture more frequently (i.e., on a greater number of trials), these also have to be actively suppressed more frequently (on a greater number of trials), giving rise to an, on average (i.e., across trials), increased inhibition effect in this condition. The idea is that a distractor that captured attention (once it is established by a post-selective analysis process that it is a distractor, rather than a target) must be actively inhibited (see Liesefeld, Liesefeld, et al., 2017, for ERP evidence for this sequence of events), so that it does no longer compete for selection. The amount of inhibition may either be adjusted to the difficulty of keeping the distractor out of the search, or it may be a fixed amount per capture incident regardless of this difficulty. Future work is required to distinguish between these possibilities.

Conclusions

While same-dimension distractors cause four times greater interference than different-dimension distractors, the probability-cueing effect (i.e., reduced interference by distractors in the frequent vs. the rare region) is evident with both types of distractors. However, the effect is much stronger for same-dimension distractors, which also display a robust target-location effect (slower responses to targets appearing in the frequent versus the rare distractor region). The latter is indicative of a strong component of general, spatial suppression of the frequent distractor region, which we propose, operates at the level of the master saliency map, on top of any feature-based modulations. With different-dimension distractors, by contrast, there was a probability-cueing effect but no target-location effect. While the probability-cueing effect is also attributable to an element of differential spatial suppression between the frequent and rare distractor regions, this operates at a level prior to the search-guiding master saliency map, selectively down-modulating feature-contrast signals from the distractor dimension so that they register only weakly on the master saliency map. The improved ability to suppress distractors in the frequent region appears to be acquired implicitly, without observers being consciously aware of the unequal distractor distribution; though, with very salient distractors, at least some observers may become aware of the unequal distractor distribution and deliberately increase the amount of frequent-region suppression. Given this, open questions for future work concern whether explicit information about the distribution can modulate the effect, whether the current explanatory framework generalizes to other dimensions, and whether possible alternative explanations can be dissociated via direct tracking of attention allocations and suppression mechanisms by means of event-related potentials.

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Appendix

Supplementary Introduction

When examining for distractor probability cueing, it is important to make sure that there is an effect of statistical learning of spatial cues over and above that of mere inter-trial repetitions. For instance, it is known that in, singleton-search episodes, distractor locations are inhibited or negatively tagged, increasing the time it takes for a feature contrast signal at such a location to reach the level of salience required to summon attention (Cepeda, Cave, Bichot & Kim, 1998; Kumada, 1999; see also Dent, Allen, Braithwaite & Humphreys, 2012). Thus, given that inhibitory tagging of previous distractor locations is, by definition, more likely in the region where distractors occur frequently, a (subsequent) distractor falling in this region would be more likely affected compared to a distractor in the rare distractor region – mimicking a learnt probability-cueing effect and thereby reducing distractor interference, when, in fact, the effect is driven purely by (passive) inter-trial dynamics. Goschy et al. (2014) attempted to control for this type of inter-trial effect in a dedicated experiment (their Experiment 3) in which the distractor on trial *n* (D_n) could, by design, not fall on the location of the distractor on trial *n-1* (D_{n-1}; inter-trial transition D_{n-1}–D_n). Goschy et al. indeed found that the differential interference between the frequent and rare distractor areas was reduced as a result of ruling out D_{n-1}–D_n transitions, but there remained a robust effect attributable to the learning of probability cues. However, changing the design of the experiment (as Goschy et al., 2014, did to exclude distractor-location repetitions) may have led to a change in participants' search strategy and thus to a change in the effect sizes. For this reason, we opted for another approach to eliminate inter-trial effects: in the present study, we allowed all possible cross-trial (location) transitions to occur, but partialed out the inter-trial effects by excluding potentially affected trials post-hoc from analysis. A further advantage conferred by this procedure is that it permitted us to quantify the inter-trial effects (i.e., the extent to which they account for the ‘probability-cueing’ effect) within the same experiments (participants) (i.e. without changing the experimental design).

A second caveat concerns examination for the predicted target-position effect (in the same-dimension condition). It is thought that when a salient distractor captures attention, it must be (actively) suppressed for focal attention to move on to the next most salient item, the target (see, e.g., Liesefeld, Liesefeld, et al., 2017), and this suppression affects not only the distractor location itself, but spreads laterally to the surrounding region, tailing off gradually with increasing distance from the distractor location (e.g., Gaspar & McDonald, 2014; Mathot, Hickey, & Theeuwes, 2010; Mounts, 2000). Now (with the display arrangement realized in Goschy et al., 2014, and the present study; see Figure 1), with a distractor in the frequent area, a target in the frequent area would, on average, be nearer to the distractor than a target in the rare area (in the present design as well as that of Goschy et al., 2014, the target-distractor separation around the circle on which the two singletons were arranged varied between 1 unit [target and distractor adjacent] and 4 units [target and distractor separated by three intervening stimuli on the circle] when target and distractor were located in the same area, but between 2 and 6 units when they were located in different areas). That is, a target in the same area as the distractor would be more likely affected by lateral inhibition than a target in a different area to the distractor, giving rise to slower reaction times to targets in the frequent as compared to the rare region. Critically, an additional target position effect in the same direction is also predicted by our DWA-based hypothesis for the same-dimension distractor condition.[13] Thus, to remove any confound with this effect in terms of

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[13] Note, however, that, on the DWA, the additional spatial effect should occur exclusively for same-dimension, but not different-dimension, distractors; and it should occur even for distractor-absent trials, on which there is no distractor in the display that would need to be inhibited for focal attention to be allocated to the target. The lateral-inhibition effect, by contrast, would occur equally with same- and with different-dimension distractors, but only on distractor-present, not on distractor-absent, trials. Furthermore, with a distractor in the rare area, a target in the rare area would, on average, be nearer to the distractor than a target in the frequent area and thus be more affected by lateral inhibition. While this would again predict a target position effect (RTs to rare-area targets being

lateral inhibition, analysis must be restricted to (only) such trials for which the target-distractor distance is equated between conditions with a distractor located in the frequent area and those with a distractor in the rare area. In the present study, this was done by restricting analyses to separations of 3 units (9.85° of visual angle) and 4 units (12.07°) only (there were too few trials with a separation of 2 units).

Supplementary Results

As elaborated above, in order to examine for pure statistical learning effects (here: learning of the distractor frequency distribution), potentially confounding effects – specifically, effects arising from (i) certain inter-trial transition effects as well as (ii) effects attributable to differential target-to-distractor distances between critical conditions – were eliminated from the data set. Such effects exhibited interesting differential patterns between the same- and different-dimension distractor conditions, as detailed in the following two sections.

Inter-trial effects. A major confound is likely given by (current) trials on which the distractor, D_n, appears at the location of the last distractor, $D_{n-1.}$ In such D_{n-1}–D_n transitions, the current distractor falls on a location that is inhibitorily tagged (as a result of the distractor on the previous trials falling on this position) and is therefore less potent in attracting attention and causing interference. As such transitions are more likely for the frequent than for the rare distractor area, they would enhance any differential interference effects between the frequent and the rare distractor region that might arise from statistical learning. As indicated by Goschy et al. (2014; comparison of their Experiment 2 with Experiment 1), a significant part of the

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slower than RTs to frequent-area targets), the effect is actually in the opposite direction to that predicted by the DWA-based account. On the latter, RTs to frequent-area targets should be generally slower than RTs to rare-area targets, even on distractor-absent trials and no matter whether the distractor is located in the frequent or the rare region on target-present trials.

differential interference effects between distractors in the frequent versus the rare area is indeed attributable to such D_{n-1}–D_n transitions. However, there are other inter-trial transitions (besides D_{n-1}–D_n transitions – the only ones controlled for by Goschy et al., 2014, in their Experiment 3) that may affect the magnitude of distractor interference, notably, (i) a (current) target falling at the same position as the previous distractor (D_{n-1}–T_n) and (ii) a (current) distractor falling at the same position as the previous target (T_{n-1}–D_n). Concerning case (i), given carry-over of inhibitory tagging, a (current) target falling at the same position as the previous distractor would make the current target less potent (i.e., it would take longer to achieve salience and attract focal attention). As instances of type D_{n-1}–T_n would be much more likely for the frequent distractor area, this could also skew the results regarding statistical learning of distractor frequency distributions, though in the opposite direction to D_{n-1}–D_n transitions: D_{n-1}–T_n transitions would reduce the differential distractor interference between the frequent and the rare area. Concerning case (ii), there is evidence of positive tagging (and carry-over) of the target location on a given trial (e.g., Krumenacher et al, 2009). Accordingly, a (current) distractor falling on the previous target location (T_{n-1}–D_n) would be more potent, that is, achieve salience faster and thus be more competitive for attracting focal attention. As such instances, too, are more likely for the frequent distractor area, they would again skew the results: again in the opposite direction to D_{n-1}–D_n transitions.[14]

All these effects were evident in the present data set. For instance, on distractor-present trials (i.e., on which the current distractor had the potential to produce interference), RTs (to the target) were slower when the target appeared at the same location as the last distractor (D_{n-1}–T_n) as compared to a different location (728 ms

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[14] Note that target location repetitions across successive trials (T_{n-1}–T_n) were balanced between the frequent and rare distractor areas; accordingly, such repetitions should not impact any differential distractor interference effects between the frequent and rare regions.

vs. 704 ms; $t(183) = 6.72$, $p < .001$, $d_z = 0.50$, 95% HPD [17 ms, 33 ms], $BF_{10} = 3.5 \times 10^7$), and when a distractor appeared at the same location as the last target (T_{n-1}–D_n) as compared to a different location (716 ms vs. 704 ms; $t(183) = 3.92$, $p < .001$, $d_z = 0.29$, 95% HPD [6 ms, 17 ms], $BF_{10} = 116$). Finally, RTs (to the target) were faster when the distractor appeared at the same location as the last distractor (D_{n-1}–D_n), as compared to a different location (693 ms vs. 704 ms; $t(183) = -4.34$, $p < .001$, $d_z = .32$, 95% HPD [-15 ms, -5 ms], $BF_{10} = 575$).

Interestingly, these inter-trial effects differed between the two distractor types. An ANOVA with the factors inter-trial transition type (no location repetition, D_{n-1}–T_n, D_{n-1}–D_n, T_{n-1}–D_n, T_{n-1}–T_n) and distractor type (same-dimension vs. different-dimension) revealed, besides main effects of distractor type, $F(1,182) = 44.52$, $p < .001$, $\eta^2_p = .20$, and inter-trial transition, $F(4,728) = 110.47$, $p < .001$, $\eta^2_p = .38$, the interaction to be significant, $F(4,728) = 18.01$, $p < .001$, $\eta^2_p = .09$. In follow-up *t* tests, the RTs of the four inter-trial repetition conditions were contrasted with the 'no-repetition' baseline separately for different and same-dimension distractors. For *different-dimension* distractors, compared to the baseline (668 ms), RTs were slightly slowed, by a little over 10 ms, to targets appearing at a previous distractor location (D_{n-1}–T_n: 681 ms; $t(127) = 3.50$, $p < .001$, $d_z = .31$, 95% HPD [6 ms, 20 ms], $BF_{10} = 31$), or when the current distractor appeared at a previous target location (T_{n-1}–D_n: 680 ms; $t(127) = 4.14$, $p < .001$, $d_z = 0.37$, 95% HPD [7 ms, 19 ms], $BF_{10} = 263$). There was little facilitation (-2 ms) when the current distractor appeared at the previous distractor location (D_{n-1}–D_n: 666 ms; $t(127) = -0.46$, $p = .644$, $d_z = .04$, 95% HPD [-6 ms, 5 ms], $BF_{10} = 0.11$), but substantial facilitation (-49 ms) when the current target appeared at the previous target location (619 ms; $t(127) = -11.08$, $p < .001$, $d_z = .98$, 95% HPD [-57 ms, -40 ms], $BF_{10} = 2.21 \times 10^9$). For *same-dimension* distractors, compared to the baseline (789 ms), RTs were substantially slowed, by over 50 ms, when the current target appeared at the previous distractor location (D_{n-1}–T_n: 842 ms; $t(55) = 6.85$, $p < .001$, $d_z = .91$, 95% HPD [37 ms, 69 ms], BF =

1795702), while there was relatively little slowing (9 ms) when the current distractor appeared at the previous target location (T_{n-1}–D_n: 798 ms; $t(55) = 1.35$, $p = .182$, $d_z = 0.18$, 95% HPD [-5 ms, 22 ms], $BF_{10} = 0.34$). There was sizeable facilitation (-32 ms) when the current distractor appeared at the previous distractor location (D_{n-1}–D_n: 757 ms; $t(55) = -6.69$, $p < .001$, $d_z = 0.89$, 95% HPD [-40 ms, -21 ms], BF_{10} = 1019639), and even greater facilitation (-70 ms) when the current target appeared at the previous target location (T_{n-1}–T_n: 719 ms; $t(55) = -8.08$, $p < .001$, $d_z = 1.08$, 95% HPD [-85 ms, -50 ms], $BF_{10} = 1.54 \times 10^8$). Thus, the interaction effect derives from the fact that especially the (inter-trial) distractor-location inhibition (D_{n-1}–T_n trials: 53 ms vs. 13 ms; D_{n-1}–D_n trials: -32 ms vs. -2 ms), and to some extent also the target-location facilitation (at least on T_{n-1}–T_n trials: -49 ms vs. -70 ms), was greatly increased in the same-, relative to the different-, dimension condition (distractor-location inhibition was increased by a factor of at least 4!).

As already said, location transitions involving the distractor happened more often in the frequent distractor area (therefore confounding the results). On average across participants, a target appeared at the same location as the previous distractor absolutely more often in the frequent ($N = 30$) compared to the rare distractor region ($N = 4$); a distractor appeared at the same location as the previous distractor much more often in the frequent ($N = 59$) than in the rare distractor region ($N = 1$); also, a distractor appeared in the same location as the previous target absolutely (and relatively somewhat) more often in the frequent distractor region ($N = 39$) than in the rare distractor region ($N = 4$). Given their distribution imbalances, all these inter-trial transitions should be – and, in the present study, were – excluded for the analysis of 'pure' statistical learning effects.[15]

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[15] Note that, in the present study, the results remained similar after removal, which is because the two effects of distractor-distractor transitions (D_{n-1}–D_n) facilitating processing and distractor-target transitions (D_{n-1}–T_n) impairing processing (in the frequent area) largely cancel each other out. Also note that target-target (T_{n-1}–T_n) transitions do not affect the probability-cueing effect, as such transitions are equally likely in both (the frequent and the rare) distractor areas.

Target-to-distractor distance effects. Another confound in the present study may be that targets are subject to differential amounts of lateral inhibition (arising from the suppression of distractors that captured attention) depending on whether they are located within the same area as the distractor (i.e., both in the frequent or the rare distractor area, in which case the average distance of the target to the distractor would be smaller and therefore the inhibitory influence larger) or in different areas (in which case the average distance would be larger and therefore the inhibitory influence smaller). Such lateral-inhibition effects could conceivably add to (distractor in frequent area) or take away from (distractor in rare area) the target-position effect predicted on the DWA-based account – though only under distractor-present conditions!

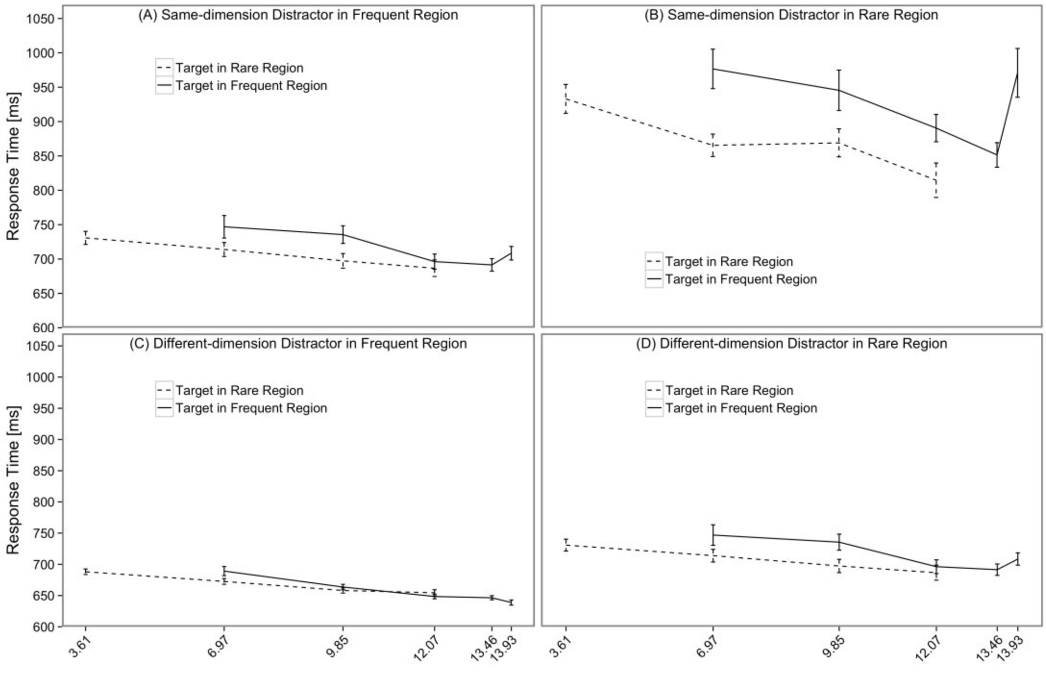

Figure A1. Mean RTs as a function of target-to-distractor distance (in degrees of visual angle), for each of the combinations of distractor location (distractor located in frequent vs. rare region: left- vs. right-hand panels) × target location (target located in frequent vs. rare distractor region), separately for the two distractor types (same- vs. different-dimension: upper vs. lower panels).

For the present data, the lateral-inhibition effects are depicted in Figure A1. Each panel presents RT as a function of the distance (in degrees of visual angle) of the target from the distractor, separately for targets located in the frequent and targets located in the rare distractor area; these functions are shown separately for same- and different-dimension distractors (upper and lower panels) appearing in the frequent and rare distractor areas (left and right panels), respectively. As can be seen from the (fairly linear) decreases in RTs with increasing target-distractor separation, lateral-inhibition effects do manifest in all conditions.[16] Furthermore, the amount of lateral inhibition, measured in terms of the rate of RT decrease per unit of distance (i.e., degrees of visual angle), appears overall more marked for same- than for different-dimension distractors (-12.99 ms/° vs -4.72 ms/°; $t(72.73) = -6.1$, $p < .001$, $d_z = 1.18$, 95% HPD [-9.897 ms/°, -7.582 ms/°], BF10 = 1.193e+09[17]).

To make sure we compare like with like in the critical analyses of distractor-interference effects, we went on to examine RTs as a function of distractor location (distractor-in-frequent- vs. distractor-in-rare-area) × target–distractor distance (9.85° vs. 12.07°) × target position (same vs. opposite area with respect to distractor). The latter variable was included as, conceivably, the gradient of the inhibition applied might differ between the two distractor areas – in which case lateral inhibition would vary even for equivalent distances. Distractor location × distance × target position (repeated-measures) ANOVAs performed separately for same- and different-dimension distractors failed to reveal any interactions between target position and distance (target position × distance: $F(1,47) = 0.71$ and, respectively, $F(1,89) = 0.02$, ps > .1; distractor location × target position × distance:

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[16] This pattern is consistent across the range of distances for conditions with a distractor in the frequent area, for which we have relatively reliable estimates. The one deviant value for the greatest separation with a same-dimension distractor in the rare area and a target in the frequent area is likely attributable to a measurement error, given the few trials available for this extreme, distractor-in-rare-area condition.

[17] Slopes calculated excluding the most extreme distance of 13.93°.

$F(1,47) = 0.04$ and, respectively, $F(1,89) = 1.22$, $p = .272$).[18] That is, there was no evidence of a modulation of any target-position effects by distractor-to-target distance (the main effect of target position was significant for the same-dimension, but not for the different-dimension condition: $F(1,47) = 11.29$, $p = .002$, vs. $F(1,89) = 0.30$, $p = .585$). Restated, for equivalent distractor-to-target distances (and for a given type of distractor appearing in a given area), target-position effects, if any, are simply additive to the lateral-inhibition effects. Thus, by including in the analysis of target-position effects only 'equated' distances, we can be confident that any effects on target processing revealed are not confounded by differential amounts of lateral inhibition when the target is located within the same versus the opposite area to the distractor.

Accordingly, prior to analysis of the distractor interference effects reported below, we dealt with (potential) *inter-trial transition confounds* by eliminating all trials on which (i) the current distractor appeared at the exact same position as the previous distractor (D_{n-1}–D_n); (ii) the current target appeared at the exact same position as the previous distractor (D_{n-1}–T_n); and (iii) the current distractor appears at the exact same position as the previous target (T_{n-1}–D_n) – which resulted in the removal of 17% of the trials. Furthermore, to deal with *lateral-inhibition confounds*, we only included (distractor-to-target) distances in the analysis that were common to the conditions with targets in the frequent and targets in the rare distractor area – specifically, distances of 9.85°, and 12.07°, for all distractor-type × distractor-position combinations. The latter two distances were included because missing values were minimal at these distances (only one participant had to be excluded) and the distances could be effectively equated between the target-in-frequent- and target-in-rare-distractor-area conditions. Including only these two, equated

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[18] Due to missing values, the number of observers that could be entered into these analyses was reduced from 56 to 48 in the same-dimension distractor condition and from 128 to 90 in the different-dimension condition.

distances in the distractor-interference analysis led to the omission of a further 26% of the trials.

Author contributions

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment, conducted the study (with help of Mallissa Watt and Paul Ricci) and analyzed the data. Marian Sauter and Hermann Müller wrote the manuscript. MS, HM, MZ and HL revised the manuscript. Marian Sauter is the only first author.

The location probability cueing effect is revealed by ERP components

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Abstract

Observers in a search task can exploit uneven distributions of target locations in order to facilitate search performance (f.e. Geng & Behrmann, 2002). A study by Sauter et al. (accepted) investigated the mechanisms underlying this probability cueing of distractor locations and found a coupling of space- and dimension-based suppression mechanisms depending on whether the distractor is defined in the same or different visual dimension as compared to the target. If target and distractor are defined in the same dimension, global space-based suppression dominates and if they are defined in different dimensions, a more specific dimension-based suppression mechanism can be employed. The present study sought to investigate whether the learned suppression of the frequent distractor region, that is spatial in nature, will be reflected in event-related potentials, specifically, the N2pc and P_D components. The N2pc is a common neurophysiological marker to measure the allocation of visuospatial attention (Luck and Hillyard, 1994) and the related P_D is a positive going deflection elicited shortly after attention is allocated to a distractor and interpreted as evidence of active distractor suppression (Hickey, Lollo, & McDonald, 2009). The present study reveals that attention was allocated to frequent and rare distractors, but more consistently to frequent distractors. There was a distractor-P_D elicited for both frequent and rare distractors, indicative of active top-down suppression. The N2pc amplitude was also larger for frequent distractors as compared to rare distractors, which could indicate a larger amount of attentional resources required to attend to the distractor stimulus in the region which is suppressed on a global-salience level. The results generally speak in favor of a more efficient global-salience distractor-handling to be recruitable for learned distractors.

Keywords: probability cueing, location suppression, N2pc

Introduction

In visual pop-out search, it is well-established that observers can exploit uneven distributions of target locations in order to facilitate search performance: targets are detected faster at locations where they appear more frequently (Anderson & Druker, 2010; Fecteau, Korjoukov, & Roelfsema, 2009; Geng & Behrmann, 2002; 2005) – providing evidence for what has been termed location probability cueing (Geng & Behrmann, 2002). Likewise, task-irrelevant distractors can be better suppressed at locations where they appear more often. In a typical probability-cueing study (Goschy et al, 2014, Sauter et al, accepted), the authors present a slightly tilted (f.e., orientation-defined) gray target bar among vertical gray non-targets arranged around concentric circles. In half of the search arrays, one of the vertical non-targets is red, serving as a highly salient color-defined distractor. The distribution of the distractor location is manipulated in such a way that distractors appeared with 90% probability in one half of the display (frequent region) and with 10% in the other (rare region). They find distractor interference to be significantly reduced when the distractor was presented in the frequent compared to the rare region. This finding suggests that we cannot only exploit uneven spatial distributions when they are directly related to the response-relevant target but also in shielding from distracting influences from task-irrelevant non-targets.

The study by Sauter et al. (accepted) investigated the mechanisms underlying this probability cueing of distractor locations and found a coupling of space- and dimension-based suppression mechanisms depending on whether the distractor is defined in the same or different dimension as compared to the target. Using a different-dimension (i.e. color) distractor, they only found the distractor to be suppressed on a dimensional level while using a same-dimension distractor, they found spatial suppression for the entire display region. This means that the search target was also suppressed when appearing in this region.

A common neurophysiological marker to measure the allocation of visuospatial attention is the N2pc component of the event-related potential (Luck and Hillyard, 1994), manifested as a negative-going deflection in the EEG signal contralateral to the stimulus. A related component is the P_D, which is a positive going deflection elicited shortly after attention is allocated to a distractor (often instead of a distractor-N2pc). It is interpreted as evidence of active distractor suppression (Hickey, Lollo, & McDonald, 2009). In an investigation using the additional singleton paradigm, Hickey et al. (2006) showed observers search displays containing the target stimulus on the one hemifield while a distractor was in the other hemifield. They found that both stimuli elicited N2pc waves. Importantly, the distractor N2pc appeared before the target-N2pc, leading to the conclusion that the distractor first attracted attention, before it was re-allocated to the target. Recently, another study (Liesefeld, Liesefeld, Töllner and Müller, 2017) tracked capture and re-allocation dynamics including a modified approach: They showed either target or distractor laterally in one hemifield while the other one appeared on the vertical midline (similar to Hickey et al., 2006). An object on the midline does not elicit an N2pc, so it is possible to isolate distractor-related activity. They found that attention was reliably allocated to the distractor (distractor-N2pc), which was subsequently suppressed (P_D). Additionally, they revealed that suppression of the distractor and attentional allocation towards the target seemed to happen in parallel rather than serially.

The present study ought to investigate how the probability cueing of distractor locations manifests in the N2pc and P_D. Since the frequent distractor region seems to be suppressed on a global-salience level reducing all objects' saliency in this region, we did not expect this to influence the N2pc amplitude per se. Also, it is not clear whether the amplitude of these ERP components reflects the degree of suppression, its efficiency or whether it is purely circumstantial. For example, research into N2pc amplitude has shown that close proximity between target and distractor may decrease the N2pc amplitude (Hilimire, 2009). A close proximity between target and distractor is more apparent in the frequent distractor region, so possibly N2pc amplitude in this region will be decreased. However, another study did not find amplitude to be influenced by proximity (Mazza et al., 2008), indicating this effect might be task-dependent. It is plausible that the EEG correlates with the behavioral data. Based on the faster response times for frequent distractors as compared to rare distractors, it could be that the process of allocating attention to the frequent distractor (in order to suppress it) and subsequently re-allocate to the target is faster or starts earlier.

We investigated these possibilities employing the same paradigm used by Liesefeld et al. (2017) with an additional distractor frequency manipulation. This means, while EEG was recorded, participants completed a compound search task looking for a slightly tilted target, while a (highly salient) horizontal distractor appeared on 50% of the displays. On distractor-present trials, the distractor appeared on the top semicircle with a probability of 90% and on the bottom semicircle with a probability of 10% (counterbalanced across participants). This allowed us to directly compare N2pc and PD components elicited by target and distractors in the learned (i.e. suppressed) frequent region and in the rare (i.e. unsuppressed) region.

Methods

Participants

One participant had to be excluded because of technical problems during recording. Thus, 15 (12 female, 3 male) right-handed observers, with a median age of 25 (range: 19–38) years were included in the final analysis. They were recruited at the Ludwig Maximilian University Munich. All of them reported normal or corrected-to-normal (color) vision and gave prior informed consent. They received 8€ per hour or course credit in compensation.

Apparatus

The experiment was conducted in a sound-reduced, moderately lit test chamber. The search displays were presented on a CRT monitor at 1024 px × 768 px screen resolution and a refresh rate of 120 Hz. Stimuli were generated using OpenSesame 3.0 (Mathôt, S., Schreij, D., & Theeuwes, J., 2012) using a PsychoPy (Peirce, 2007) backend. The observers issued their responses using a regular mouse by pressing the “left” or “right” button with their left- or right-hand thumb, respectively (counterbalanced across participants).

Stimuli

The stimulus displays were presented on a black background. They consisted of light blue (RGB: 127, 127, 127; CIE [Yxy]: 20.22, 0.32, 0.34) vertical non-target bars (0.125° of visual angle wide, 0.675° high), with their centers equidistantly arranged on four imaginary concentric circles with radii of 0.5°, 1°, 2° and 3°, comprising of 6, 12, 18 and 24 bars, respectively. The center of the circles was occupied by a fixation cross. In every bar, there was a gap of 0.125° in height, which was randomly located 0.125° from the top or bottom of the bar. The target differed from the non-targets by its unique orientation, randomly assigned on each trial: it was tilted 12° to either the right or the left. If a singleton distractor was present, one of the non-targets was tilted 90° (horizontal) instead of vertical.

Design

The experiment consisted of 2000 trials in 20 blocks. The frequency distribution of the distractor was manipulated as a between-subject factor. Distractor frequencies were differently distributed in the top and the bottom half of the display, ranging from the 10 o’clock to the 2 o’clock positions versus the 4 o’clock to the 8 o’clock positions on the second inner circle (see Figure 1). For half of the participants, the top semicircle was the frequent distractor area (10 o'clock to the 2 o'clock positions) and for the other half, the bottom semicircle was the frequent distractor area (4 o'clock to the 8 o'clock positions). Neither the distractor nor the target could appear at the 3 o'clock and 9 o'clock positions as these positions could not be unambiguously assigned to the frequent or rare area. A distractor was present in a random 50% of the displays per block. If a distractor was present, it appeared in the frequent area about 90% of the time ('frequent distractors') and in the rare area about 10% of the time ('rare distractors'). To elicit clean N2pcs to the target or distractor, either the distractor or the target appeared in a middle position (i.e. 12 o'clock or 6 o'clock) and the other appeared laterally. The target appeared equally often in both areas, with an equal probability for all 10 possible positions, but it never occurred at the same position as the distractor (which is impossible by design). The trial sequence within each block was randomized.

Procedure

All observers were instructed that their task was to judge whether the target bar was interrupted (by a gap) at the top or the bottom. When it was interrupted at the bottom, participants had to press the "left" button; when it was interrupted at the top, they had to press the "right" button (counterbalanced between participants). They were informed that on some trials, there would be a horizontal distractor bar, which they should simply ignore, as it would be irrelevant to their task. They were not informed that the distractor would be more likely to appear in one particular semi-circle.

All trials started with a white fixation cross in the middle of the screen for a random duration between 700 ms and 1100 ms. Then the search display appeared and stayed on until the observer responded. If the answer was incorrect, the word "Error" appeared in the center of the screen for 500 ms. The next trial started without a delay. After each block of trials, observers received RT and accuracy feedback and could resume the experiment at their own discretion. After 10 blocks, they had to take a longer break of at least 10 minutes. After completing the computer experiment, participants filled in a brief questionnaire to check whether they had any explicit knowledge of the singleton distractors' prevalence and spatial frequency distribution.

Analysis

Behavioral

For the analyses presented below, we chose Cohen's d to assess effect sizes. Apart from classical frequentist measures, to address issues raised by the ongoing "replication crisis", we further report 95% highest posterior density intervals (HPD) with the "coda" package (Plummer et al, 2006) for R (R Core Team, 2014) as the credibility interval which is a Bayesian parameter estimate (similar to confidence intervals) and report JZS BF_{10} Bayes factors (Rouder et al, 2009) with the BayesFactor package (Morey and Rouder, 2015) for R for our critical t-tests.

EEG

The electroencephalogram (EEG) was recorded continuously via 58 Ag/AgCl electrodes positioned according to the international 10-10 system. A left-mastoid reference was used during recording, and signals were re-referenced offline to the average of both mastoids. Vertical and horizontal ocular artefacts were monitored via four additional electrodes above and below the left eye and at the outer canthi of both eyes. All impedances were kept below 10 kΩ. Signals were amplified (250-Hz low-pass filter, 10-s time constant; BrainAmp DC, BrainProducts, Munich, Germany) and sampled at 1,000 Hz. EEG data were processed with custom-written Matlab (The Mathworks, Natick, MA) code using functions from EEGLAB (Delorme and Makeig, 2004) and Fieldtrip (Oostenveld, Fries, Maris, and Schoffelen, 2011). We applied 0.5-Hz high-pass and 40-Hz low-pass FIR filters

(EEGLAB default), ran an independent component analysis (ICA; EEGLAB, extended mode) and removed ICA components representing blinks or horizontal eye movements. After these pre-processing steps on the continuous EEG, data were segmented into epochs from −200 ms to 700 ms relative to search display onset and baseline-corrected with respect to the pre-stimulus interval. Trials with artefacts in the analysed channels (PO7/8; voltage steps larger than 50 µV per sampling point, activity changes less than 0.5 µV within a 500-ms time window, or absolute amplitude exceeding ± 30 µV), horizontal eye movements (detected prior to the ICA), or incorrect responses were excluded (6.7% overall).

To extract ERPs, EEG epochs from each condition were averaged separately for contralateral and ipsilateral electrodes (relative to the distractor in the midline-target/lateral-distractor condition and relative to the target in all other conditions), and the resulting individual ipsilateral ERPs were subtracted from the contralateral ERPs. Lateralized components were analysed in these difference waves at electrode sites PO7/8. For component latency estimation, we used 50%-area latency (Luck, 2005, pp. 239–242), where component area was defined as the region bounded by the ERP, a threshold set at 30% of the component's amplitude, and the two time points where the ERP crossed the threshold (on- and offset of the respective component). The search for on- and offsets started at the highest local peak within the search interval and proceeded towards both search intervals. If no on- or offset was found, the respective search interval border served as the boundary instead. The pattern of results (including all decisions on statistical significance) was the same with 30%-amplitude latency (component onset). We report area latency, because it is more representative for the distribution of latencies. Whereas onset latency is biased towards the earliest component onsets, area latency reflects the median latency of a component.

To determine analysis windows for amplitudes of the components of interest, we performed 50%-area latency detection on the strongest component of the respective polarity in the respective grand-average difference wave and defined amplitudes as the mean activity in a 30-ms window centered on these time points. For statistical tests on differences in component latencies, these latencies were determined for each participant within a common time window encompassing on- and offsets of all analysed components (163–446 ms). As we had strong a- priori hypotheses about the direction of effects (e.g., we predicted that a lateralized target would elicit a negative component [the target N2pc] in the difference wave and that the target N2pc would be delayed on distractor-present trials), t-tests were performed one-tailed, except for tests predicted to be non-significant or calculated post hoc (as indicated).

Results

Behavioral

Our main prediction for the behavioral results, was that the probability-cueing effect (evidenced by reduced interference by distractors in the frequent vs. the rare area) will be replicated in the present study. Mean error rates were influenced by distractor condition (frequent area, rare area, absent), $F(2,28) = 8.14$, $p = .005$ but not target position, $F(1,14) = 0.90$, $p = .360$. Error rates were highest in the rare area (5.9%) and higher in the frequent area (5.1%) compared to absent distractors (3.7%). Because this trend is the same for reaction times (see below), a condition-specific speed-accuracy trade-off cannot explain this effect. All error trials were then excluded from further analysis (4.5%).

To ascertain that distractors generally caused interference (c.f. Figure 1), we directly compared RTs on distractor-present trials with those on distractor-absent trials: RTs for trials when a distractor was present were slower compared to when the distractor was absent (710 ms vs. 607 ms; $t(14) = 11.83$, $p < .001$, $d_z = 3.1$, $BF_{10} =$

2074116, 95% HPD [80 ms, 120 ms]). To directly test for a probability cueing effect, we contrasted the frequent versus rare distractor-present conditions: RTs were slower when the distractor was in the rare area compared to the frequent area (746 ms, 674 ms; $t(14) = 7.50$, $p < .001$, $d_z = 1.94$, $BF_{10} = 13572$, 95% HPD [48 ms, 89 ms]).

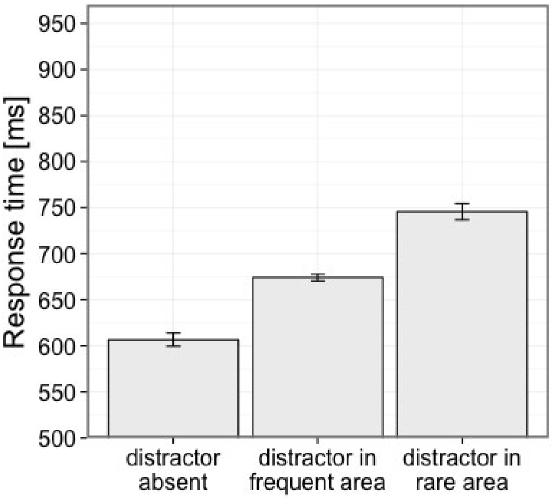

Figure 1. Response times as a function of the distractor condition (absent vs. distractor in frequent region vs. distractor in rare region). Error bars indicate within-subject standard error of the mean (SEM; Morey, 2008).

Event-related potentials

First, we tested whether the orientation distractor captured attention in both distractor conditions (frequent region vs. rare region). Indeed, a prominent distractor N2pc emerged in the midline-target/lateral-distractor condition for distractors in the frequent area (−1.15 μV; $t(14) = -4.20$, $p < .001$, $d = -1.08$) but there was only a small trend for distractors in the rare area(-0.42 μV; $t(14) = -1.52$, $p = .075$, $d = -0.39$). Importantly, the frequent distractor N2pc had a significantly higher amplitude than the rare distractor N2pc (0.73 μV; $t(14) = 1.93$, $p = .037$, $d = 0.50$) and emerged earlier (-56 ms; $t(14) = -2.67$, $p = .009$, $d = -0.69$). Further, a prominent distractor PD emerged on midline-target/lateral-distractor trials, importantly, both for frequent distractors (1.18 μV; $t(14) = 3.81$, $p = .001$, $d = 0.98$)

and rare distractors (1.22 μV; t(14) = 3.15, p = .004, d = 0.81). For frequent distractors, the PD emerged clearly later (94 ms) than the N2pc, t(14) = 4.17, p < .001, d = 1.08. But for rare distractors there was no clear (54 ms) latency shift, t(14) = 1.63, p = .063, d = 0.42. There was also no difference in PD amplitude between frequent and rare distractors (0.04 μV; t(14) = 0.17, p = .434, dz = 0.04).

In the distractor-absent condition, the lateral target elicited a pronounced N2pc for targets that appeared in the frequent distractor region (-1.43 μV), t(14) = -4.67, p < .001, d = -1.21 and targets that appeared in the rare distractor region (−0.68 μV), t(14) = -2.65, p = .010, d = -0.68, indicating that spatial attention was consistently directed to the target. Such a target N2pc also emerged on lateral-target/midline-distractor trials for both targets that appeared in the frequent distractor region (-0.83 μV), t(14) = -3.52, p = .002, d = -0.91, and targets that appeared in the rare distractor region (-0.59 μV), t(14) = -4.03, p = .001, d = -1.04. Lastly, when the distractor was absent, there was no latency difference in the N2pc components of frequent versus rare distractors (1 ms; t(14) = 0.11, p = .458, dz = 0.03). When a distractor was present, the target-N2pc was delayed by 87 ms for targets that appeared in the frequent distractor region (t(14) = -6.99, p < .001, d = -1.81) but was not delayed for targets that appeared in the rare distractor region (19 ms; t(14) = -1.23, p = .120, d = -0.32). Additionally, the N2pc for targets that appeared in the frequent region was generally delayed by 67 ms when compared to targets that appeared in the rare distractor region, t(14) = 3.72, p = .001, d = 0.96.

We predicted that in distractor-present displays, attention would be allocated first to the (more salient) distractor and only afterwards to the (less salient) target. To examine whether the distractor was indeed attended before the target, we compared the latency of the distractor N2pc in the midline-target/lateral-distractor condition to the latency of the target N2pc in the lateral-target/midline-distractor condition. The distractor N2pc preceded the target N2pc (compare the respective N2pcs in

Fig. 2A and Fig. 2B) for frequent distractors by 107 ms, t(14) = -5.08, p < .001, dz = -1.31 but not for rare distractors (16 ms; t(14) = -0.58, p = .286, dz = 0.15.

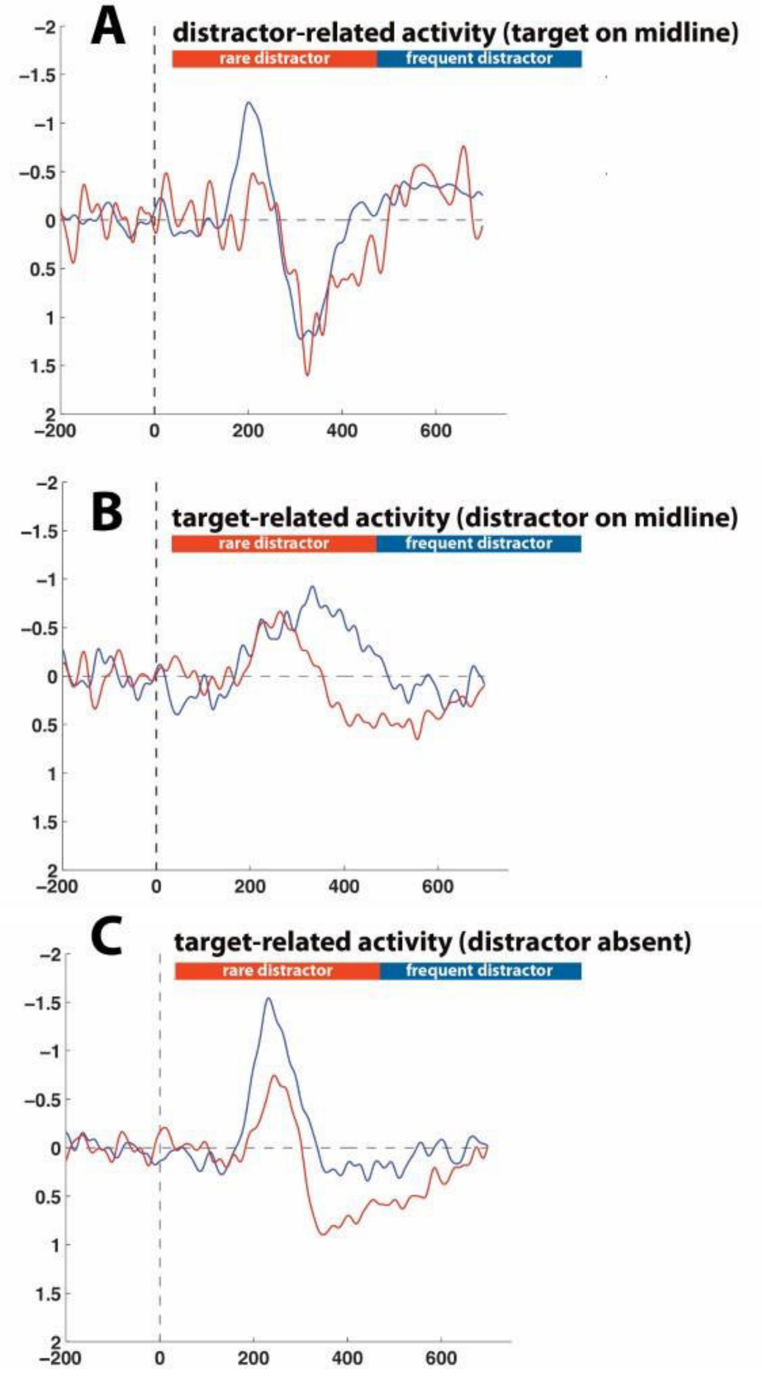

Figure 2. Difference waves in microvolt (contralateral minus ipsilateral) at the electrodes PO7/PO8 for the three conditions (A-C). The blue line corresponds to the distractor (A) or target (B, C) appearing in the frequent distractor region and the red line corresponds to the stimuli appearing in the rare distractor region. X-axis numerals indicate time in milliseconds, the vertical striped line indicates onset of the search display.

Discussion

The present study sought to investigate whether the learned suppression of the frequent distractor region, that is spatial in nature, will be reflected in the N2pc component in some way. The behavioral results indicate that frequent and rare distractors both reliably captured attention and the frequent/rare distractor distribution was learned: There was a probability cueing effect of 74 ms, which is smaller compared to the effects found by Sauter and colleagues (2018) but importantly, is attributable to statistical learning alone, as short-term inter-trial repetition effects were rendered impossible by the experimental design.

Along the lines of Liesefeld et al. (2017), we found that attention was allocated to the distractors as we found the N2pc component to be elicited reliably for frequent distractors and as a statistical trend for rare distractors. In line with our hypotheses, the N2pc for frequent distractors as compared to rare distractors was elicited earlier. This speaks in favor of a reliable mechanism for distractor-interference-handling to be in place.

There was a consistent distractor-P_D elicited for both frequent and rare distractors, meaning that active top-down suppression was responsible for continuing with the next, less salient, item in the search display. This supports more evidence for the only study reporting a distractor-P_D following a distractor-N2pc (Liesefeld et al., 2017). The actual distractor suppression, as revealed by the distractor-P_D, seems to happen later for distractors in the frequent region (94 ms after distractor-N2pc) compared to distractors in the rare region (54 ms after distractor-N2pc; although only numerically), but since it still appears earlier in the frequent region (318 ms) than in the rare region (335 ms) after stimulus onset, this cannot be seen as conflicting evidence to the global-salience suppression explanation.

The N2pc amplitude was also larger for frequent distractors as compared to rare distractors, which could potentially indicate a larger amount of attentional resources required to attend to the distractor stimulus in the region which is suppressed on a global-salience level. In contrast to this is an investigation by An et al. (2012) that showed the N2pc amplitude is increased by perceptual learning in the learned region compared to the unlearned region. Following this logic, it might be that the N2pc amplitude is indirectly reflecting a global salience-based mechanism that is able to act long-term on all trials, possibly even when a distractor is absent.

In conclusion, in this study, we investigated the electrophysiological markers for distractor suppression in statistically learned and suppressed distractors versus unlearned distractors. We found that distractors in the frequent (suppressed) region, elicit larger and earlier N2pc components. The results generally speak in favor of a more efficient global-salience distractor-handling to be recruitable for learned distractors. However, the results should be seen as first hypothesis-generating explorations rather than conclusive evidence as they lack convincing statistical significances in some key comparisons. Further research should include a contralateral target/distractor setup to directly compare latency shifts for the N2pc components within a single trial.

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Author contributions

Marian Sauter, Heinrich Liesefeld, and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment, conducted the study and analyzed the behavioral data. Marian Sauter and Heinrich Liesefeld analyzed the EEG data. Marian Sauter and Heinrich Liesefeld wrote the manuscript.

Location probability cueing persists over time for same-dimension but not different-dimension distractors

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Abstract

It was shown previously that observers can learn to exploit an uneven spatial distribution of singleton distractors (90% in one half, 10% in the other half of the display) to better shield visual search from distractors in the frequent versus the rare region (i.e., *distractor location probability cueing;* Sauter et al., accepted). However, with distractors defined in the same dimension as the search target, this comes at the cost of impaired detection of targets in the frequent region. In three experiments, the present study investigated the learning and unlearning of *distractor location probability cueing* and the carry-over of cueing effects from same- to different-dimension distractors. All experiments involved visual search for an orientation-defined singleton *target* in the presence of either a more salient color-defined (different-dimension) or orientation-defined (same-dimension) *distractor* singleton, and all were divided into a learning session and a subsequent test session. The present study showed that with same-dimension (but not with different-dimension) distractors, the acquired cueing effect persists over a 24-hour break between the training and test session and takes several hundred trials to be unlearned when the distribution is changed to even (50%/50%) in the test session. Furthermore, the cueing effect (and the target location effect) carries over from learning with same-dimension distractors to test with different-dimension distractors. This pattern indicates that the learnt distractor suppression effects are implemented at different levels in the hierarchical architecture of search guidance: the master-saliency map with same-dimension distractors vs. a dimension-based level below the saliency map with different-dimension distractors.

Introduction

In visual search for singleton, pop-out targets, observers are able to learn, over time, statistical regularities in the locations of highly salient but task-irrelevant singletons (henceforth referred to as 'distractors') that compete with the target for attentional selection. This learning effect is expressed in reduced interference, that is, relatively faster reaction times (RTs), when the distractor on a given trial occurs at/within 'frequent' compared to 'rare' distractor locations/regions of the search display (e.g., Ferrante, Patacca, Di Caro, Della Libera, Santandrea, & Chelazzi, 2018; Goschy, Bakos, Müller, & Zehetleitner, 2014; Leber, Gwinn, Hong, & O'Toole, 2016; Wang & Theeuwes, 2018). Goschy et al. (2014) termed this 'distractor location probability cueing' (in analogy to Geng & Behrmann, 2005, who used the label 'target location probability cueing' to refer to the statistical learning of likely target locations in visual search).

Typically in these so-called 'additional-singleton' tasks, the attributes singling out the distractor from the background items (henceforth referred to as 'non-targets') are quite distinct from those defining the target. In the majority of studies since Theeuwes' (1992) pioneering work, the target was defined by an aspect of form (e.g., shape, orientation), whereas the distractor was defined by color, that is, in a different visual dimension to the target.[19] In Goschy et al. (2014), the 34 non-target items were all vertical grey bars. The target was the only bar having a 12° tilt to the left or the right from the vertical (i.e., it was orientation-defined), while the distractor was the only red (vertical) bar (i.e., it was color-defined and thus, relative to the target-defining dimension, a 'different-dimension distractor').[20] More

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[19] This applies, for instance, to most of the electrophysiological studies of attentional capture (e.g., Hickey, McDonald, & Theeuwes, 2006; Kiss, Grubert, Petersen, & Eimer, 2012; Jannati, Gaspar, & McDonald, 2013; Burra & Kerzel, 2013; Wykowska & Schubö, 2011).

[20] See also Wang & Theeuwes (2018) and Ferrante et al. (2018), who examined search for a shape singleton target in the presence of a color-defined, i.e., different-dimension, distractor that was highly likely to appear at one specific (frequent-disractor) location. In Goschy et al. (2014), by

recently, Sauter, Liesefeld, Zehetleitner, and Müller (2018) extended Goschy et al.'s (2014) paradigm to distractors defined in the same visual dimension as the target by replacing the color-defined (*red* vertical) distractor by an orientation-defined (a *horizontal* gray) distractor. Given that the orientation difference of the distractor to the non-targets (horizontal vs. vertical) was larger than that of the target (12° tilt vs. vertical), the distractor was more salient than the target (with the latter still affording 'pop-out', i.e., set-size-independent search; see Liesefeld, Moran, Usher, Müller, & Zehetleitner, 2016). Although Sauter et al. (accepted) found such 'same-dimension distractors' to cause massive interference (over 4 times the interference caused by different-dimension distractors), participants nevertheless learned to reduce the interference generated by distractors that appeared in the frequent distractor region compared to distractors in the rare region. Additionally, with same-dimension distractors, while the interference caused by distractors in the frequent region was reduced, there was also a cost in terms of the speed of target processing: RTs were slower to targets in the frequent region compared to targets in the rare region. Crucially, this was even the case on trials on which no distractor was actually present in the display (distractor-absent trials). This effect pattern did not exist with different-dimension distractors, for which there was just a reduction of interference for distractors in the frequent as compared to the rare region. Sauter et al. (accepted) took this differential effect pattern to conclude that interference reduction relies on fundamentally different mechanisms with same- as compared to different-dimension distractors.

In principle, the interference reduction might be based on stronger suppression on any of three levels: inhibition of *distractor-defining features* within the frequent (as compared to the rare) distractor area, down-modulation of feature-contrast signals in the *distractor-defining dimension*, or inhibition of 'dimension- and feature-less'

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contrast, color-defined distractors were more likely to appear in a whole display region (encompassing multiple possible locations).

saliency signals on the *search-guiding attentional priority, or 'master saliency', map*. The fact that, with same-dimension distractors, the reduction of distractor interference was accompanied by impaired target processing rules out feature-based suppression as a general account of the findings: if the distractor-defining feature could be selectively inhibited, it should not have mattered whether the distractor was defined in a different or the same dimension as the target. Likewise, the fact that, with different-dimension distractors, distractor interference was reduced *without* affecting target processing rules out master map inhibition as a general account of the findings: if the master map is inhibited, target processing should be impaired not only with same-, but also with different-dimension distractors. By contrast, dimension-based suppression (e.g., Müller et al., 2009; Zehetleitner et al., 2012) could account for the findings. The notion of dimension-based suppression derives from the 'dimension-weighting account' (DWA) of Müller and colleagues[21]. On this account, local feature contrast signals (coding, e.g., the orientation difference of a horizontal bar to the vertical bars in its surround) are transferred in a *dimensionally weighted* fashion to the (supra-dimensional) master saliency map, which sums the dimensionally weighted signals to determine overall-

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[21] This account, developed by Müller and colleagues (e.g., Found & Müller, 1996; Krummenacher, Müller, & Heller, 2001, 2002; Müller, Heller, & Ziegler, 1995; Müller, Reimann, & Krummenacher, 2003), assumes that the allocation of attention to locations in the search display is driven by an overall-saliency map (cf. Wolfe, 2007) which integrates feature contrast signals from the various stimulus dimensions (i.e., orientation, luminance, color, motion, etc.). The DWA posits that the feature contrast signals are weighted by dimension (rather than by individual features within a given dimension) in this saliency summation process. Thus, it is possible to down-weight a single dimension selectively, but, because of dimensionally coupled feature weighting, one cannot down-weight a specific feature in a given dimension without also down-weighting other features in this dimension. Thus, for instance in a task with orientation-defined targets and color-defined (i.e., different-dimension) distractors, one can down-weight the color dimension, reducing the saliency of color signals at the level of the overall-saliency map. If the down-weighting is strong enough, as it might be in the display region where the distractors appear more frequently, such (color) distractors will have less power to capture attention and cause less interference compared to (color) distractors occurring in the rare distractor area (where the down-weighting is less strong). However, when the distractors are defined in the same dimension as the target (e.g., the orientation dimension), this weighting strategy does not work as efficiently, because down-weighting distractor (orientation) signals also down-weights the target (orientation) signals. This the likely reason why attentional capture is extremely hard to avoid with salient same-dimension distractors (Liesefeld, Liesefeld, Töllner, & Müller, 2017).

saliency. Accordingly, down-modulating the weight of the distractor-defining dimension would not only down-modulate the distractor (feature contrast) signal in this dimension (reducing interference), but also the target signal if the target is defined within the same dimension (slowing target selection). By contrast, if the target feature is defined within a different dimension, target processing is unaffected by the down-modulation of the distractor-defining dimension. This could explain the pattern of results observed by Sauter et al. (accepted): impaired processing of an orientation-defined target when the distractor was orientation-defined (same dimension), but not when it was color-defined (different dimension). On the other hand, in the former case (with same-dimension distractors), strategic down-modulation of the orientation dimension when the target, too, is defined within this dimension would give rise to a conflict with the goal of detecting a target in this dimension. To circumvent such a conflict, observers may instead resort to a space-based inhibition strategy: suppressing any saliency signals in the frequent distractor area at the master map level. This, too, would yield impaired target processing in this area (while avoiding a goal conflict). That is, while distractor saliency (and thereby distractor interference) would be reduced for the frequent distractor region, target saliency would likewise be reduced, resulting in slower RTs to targets appearing in the frequent compared to the rare distractor region. Importantly, based on the results of Sauter et al. (accepted), one cannot tell which of these two alternatives is correct. – The present study was designed to decide this issue, by examining the learning and unlearning of distractor location probability cueing and the carry-over of cueing effects from same- to different-dimension distractors.

Rationale and Overview of the Present Study

The study followed a two-stage logic. In the first instance, it was designed to test the hypothesis that distractor location probability learning is ultimately better consolidated with same-dimension distractors as compared to different-dimension distractors. Müller et al. (2009) considered the shielding of search from distraction as a skill, that is: a set of learned, executive routines to either avoid attentional capture or efficiently deal with its consequences.[22] Now assume that same-dimension distractors give rise to greater system-internal conflict than different-dimension distractors (evidenced by the fact that, e.g., in Sauter et al., 2018, interference, measured against the distractor-absent baseline, was increased by a factor of at least 4 for same- vs. different-dimension distractors), engaging a greater degree of 'controlled processing' (Schneider & Shiffrin, 1977) to find and consolidate ways (or control routines) to minimize the interference (e.g., operating a strategy that combines space-based inhibition with feature-(template-)based activation). In the present paradigm, we predicted, this would ultimately lead to deeper spatial learning of where distractors are likely to appear with same-dimension as compared to different-dimension distractors.[23] Different-dimension distractors, by contrast, produce little conflict, as we have effective routines to deal with such distractors – such as dimension-based suppression – readily available; consequently, different-dimension distractors would lead to relatively shallow spatial learning.

One way to probe the depth of learning (in our case: statistical learning) is to assess how strong and persistent an acquired behavioral disposition, or attentional bias, is after the original 'incentive' in the task structure that gave rise to this learning (e.g., a statistical bias in some task-critical event) is removed (Leber & Egeth, 2006a,

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[22] This was based on the finding that consistent exposure to, or prior practice, with distractor displays was a major factor in reducing distractor interference (see also Zehetleitner et al., 2012). Also, with a low probability of a distractor occurring, interference was high on a given (distractor-present) trial when it was preceded by one or more distractor-absent trials, but it was reduced when it followed a distractor-present trial. Müller et al. (2009) took this pattern to suggest that when the appropriate shielding routines are activated (by encountering a distractor on a given trial), this control set remains in an active state for a while, permitting a distractor on the next trial to be dealt with efficiently.

[23] Consistent with this, Sauter et al. (2018) also found stronger evidence of explicit knowledge of the distractor distribution with same- than with different-dimension distractors.

2006b; Zellin, Conci, von Mühlenen, & Müller, 2013; Zellin, von Mühlenen, Müller, & Conci, 2014). In a comparable study to the present one, Ferrante et al. (2018), for example, observed that the learnt attentional enhancement of a frequent target location (in search for a shape-defined singleton target) did persist during an 'extinction' epoch which was administered immediately after the learning epoch and in which the target appeared equally likely at each display location. By contrast, suppression of a location at which a (color-defined) distractor singleton appeared frequently during learning was no longer significant in the extinction epoch (in which the distractor appeared equally frequently at each display location) – indicating that, at least with the different-dimension distractor used by Ferrante et al. (2018), a spatial bias in distractor suppression is unlearnt rapidly.

Adopting this logic, Experiment 1 was designed to probe the strength of learnt spatial suppression by examining for carry-over effects of distractor location probability learning from one day (day 1: learning phase) to the next (day 2, some 24 hours later: test phase), separately for a group of same-dimension distractor participants and one of different-dimension distractor participants. Importantly, participants were presented with an uneven distribution of distractors (90% of distractors in frequent area, 10% in rare area) only during the learning phase (day 1). In the test phase (day 2), the distribution was equal (50% in frequent area, 50% in rare area), so as not to provide any incentive for re-learning (and, instead, to permit unlearning to be examined). We expected a greater carry-over effect from day 1 to day 2 for same- (than for different-) dimension learners, as well as a greater number of trials necessary to unlearn the uneven distribution on day 2. The results were in line with this prediction: there was a significant carry-over effect only with same-dimension distractors, but not with different-dimension distractors. Experiment 2 went on to examine whether the failure to find a significant carry-over effect with different-dimension distractors was due to the length of the interval between the learning and the test phase, that is: would a carry-over effect be discernible when the interval is reduced (from 24 hours plus) to 5 minutes? The answer was negative, indicating that unlearning occurred rather rapidly, within the first few blocks of encountering an even distribution of different-dimension distractors, whereas it took at least double the number of blocks with same-dimension distractors.

Given these differential (un-)learning effects, Experiment 3 was designed to examine whether whatever strategy is acquired in the learning phase (on day 1) to deal with same-dimension distractors would be carried over and applied, in the test phase (on day 2), to search displays that exclusively contain different-dimension distractors (i.e., the type of distractor was switched from day 1 to day 2, in addition to the change from an uneven to an even distractor distribution). Recall, that only same-dimension distractors produce a target location effect: impaired processing of targets appearing in the frequent versus the rare distractor area. If this effect carries over from same-dimension distractor learning (on day 1) to the test with different-dimension distractors (on day 2), this would have implications for locus of the target location effect in the search architecture. The answer is: there was indeed a carry-over effect (including carry-over of the target location effect), indicative of spatial distractor suppression operating at a different level with same- versus different-dimension distractors: the master saliency map versus a dimension-based level below the saliency map.

Experiment 1

Experiment 1 was designed to test whether distractor location probability cueing carries over from one day (training) to the next (test), even if the test condition provides no (longer an) incentive to apply more distractor suppression to one as compared to the other half of the search display. For the reasons set out above, we hypothesized that there would be a stronger carry-over effect – in terms of reduced distractor interference for the previously frequent versus the previously rare display region (in the test session) – with same- than with different-dimension distractors.

Methods

Participants. 48 (28 female, 20 male)[24] right-handed observers, all students at LMU Munich, with a median age of 28 (range: 18–38) years, participated in Experiment 1. All of them reported normal or corrected-to-normal vision (including normal color vision) and gave prior informed consent (in writing). They received 8 € per hour or course credits in compensation.

Set-up. The experiment was conducted in a sound-reduced, moderately lit test chamber. The search displays were presented on a 1024px × 768px screen, at a refresh rate of 60Hz. Stimuli were generated with OpenSesame 3.1 (Mathôt, Schreij, & Theeuwes, 2012) using a Psychopy backend (Pierce, 2007). Observers issued their responses using a QWERTZ keyboard, by pressing the “y” or the “m” key with their left- or right-hand index finger, respectively. The stimulus displays were identical to those used in the study of Sauter et al. (2018), which, in terms of the present design, consisted of only an initial learning phase (without a subsequent test or unlearning phase).[25] The screen background was black. The search displays (illustrated in Figure 1) consisted of gray (RGB: 127, 127, 127; CIE [Yxy]: 13.6, 0.28, 0.32) vertical non-target bars (0.25° of visual angle wide, 1.35° high), with their geometric centers equidistantly arranged on three (imaginary) concentric circles with radii of 2°, 4°, and 6°, comprising 6, 12, and 18 bars, respectively. A further

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[24] Recruitment of 24 participants per distractor condition was based on the original study of Goschy et al. (2014), who demonstrated a convincing distractor location probability cueing effect for the ‘weaker’, different-dimension distractor condition with 24 observers. Distractor interference and, hence, the cueing modulation is ‘weaker’ in this condition than in the same-dimension distractor condition compared in Sauter et al. (2018). Note that one participant had to be excluded from analysis of the same-dimension condition owing to a loss of data.

[25] In fact, data from the learning session was part of the larger data set analyzed in the context of the Sauter et al. (2018) study.

gray bar occupied the position in the center of the three circles. In every bar, there was a gap 0.25° in size, which was randomly located 0.25° from the top or the bottom of the bar. The singleton target (present on every trial) differed from the non-targets by its unique orientation: it was (randomly) tilted 12° to either the left or the right.

A singleton distractor was present in 50% of the trials. For one group of 23 participants, one of the (gray vertical) non-targets was rotated from vertical to 90° (i.e., a horizontal bar; distractor defined in the same dimension as the target). This orientation contrast modulation ensured that the target was less salient (12° vs. vertical) than the distractor (horizontal vs. vertical; see Liesefeld et al., 2016, 2017). For the other group of 24 participants, one of the non-targets was changed from gray to red (distractor defined in a different dimension, namely color, to the orientation-defined target). Targets and distractors were presented exclusively at positions on the intermediate circle, to ensure consistent feature contrast to the non-targets in their surround (e.g., Rangelov, Müller, & Zehetleitner, 2013, 2017; Nothdurft, 1993; Liesefeld et al., 2016, 2017).

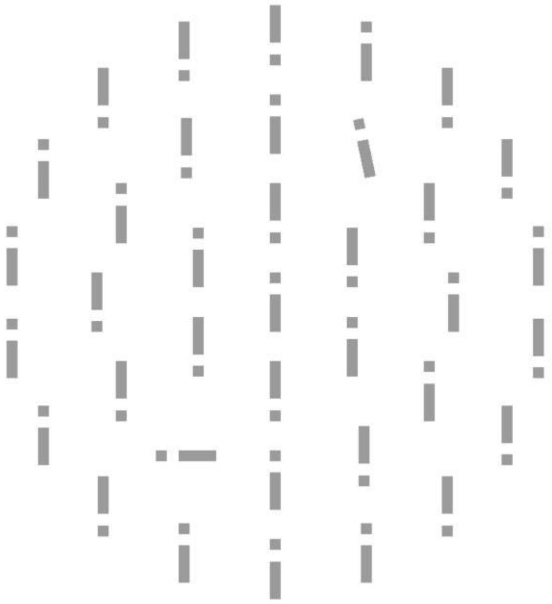

Figure 1. Example of a stimulus display. The search target is the 12°-tilted bar at the 1 o'clock position, and the (same-dimension) distractor is the 90°-tilted bar at the 7 o'clock position.

Design. The type of the singleton distractor (same vs. different dimension) was introduced as a between-subject factor. The distractor distribution in the learning session was also manipulated between subjects. The distractor frequency differed between the top half of the display (ranging from the 10 o'clock to the 2 o'clock position on the intermediate circle) and the bottom half (ranging from the 4 o'clock to the 8 o'clock position) (see Figure 1). For half of the participants within each group, the top semi-circle was the frequent and the bottom semi-circle the rare distractor area, and vice versa for the other half (see below). Neither the distractor nor the target could appear at the 3 o'clock and 9 o'clock positions, as these positions could not be unambiguously assigned to the top or bottom area of the search display.

The learning session consisted of a total of 1440 trials, separated into 12 blocks. A distractor was present in half the trials and absent in the other half. If a distractor was present, it appeared in the frequent area 90% of the time and in the rare area 10% of the time. The target appeared equally often in both areas, with an equal probability for all 10 possible positions, but it never occurred at the same position as the distractor. The test session also consisted of 12 blocks with a total of 1440 trials. Importantly, in the test session, targets and distractors occurred equally likely in the (previously, i.e., in the learning session) frequent and the (previously) rare display region. The order of the trials within each block was completely randomized.

Procedure. The experimental procedure was identical to Experiment 1 of Sauter et al. (2018). Observers were instructed, in writing and orally, that their task was to discern whether the target bar was interrupted (by a gap) at the top or the bottom.

If it was interrupted at the bottom, they were told to press the "y" key; if it was interrupted at the top, they had to press the "m" key. They were informed that on some trials, there would be a horizontal (same-dimension group) or, respectively, a red (different-dimension group) distractor bar which they should simply ignore as it would be irrelevant to the task. They were not informed that the distractor was more likely to appear in one particular region (in the top or bottom half of the display).

Each trial started with a white fixation cross in the middle of the screen for a random duration between 700ms and 1100ms. Then the search display appeared and stayed on until the observer gave a response indicating the gap position in the target bar. If the response was incorrect, the word "Fehler" (German for "Error") appeared in the center of the screen for 500ms. Thereafter, the next trial started without a delay. After each block of trials, observers received RT and accuracy feedback and could resume the experiment at their discretion.

Each participant performed both the learning and the test session, with a separation of about 24 hours between the two sessions. After completing each of the sessions, participants filled in a brief questionnaire, which was intended to gage whether they had any explicit knowledge of the singleton distractors' prevalence and spatial (frequency) distribution.

Analysis. For the analyses presented below, we opted for Cohen's *d* to assess effect sizes. Apart from classical frequentist measures, in order to address issues raised by the "replication crisis" (e.g., cf. Open Science Collaboration, 2015), we further report 95% highest posterior density (HDP) intervals (essentially a Bayesian equivalent to confidence intervals), calculated using the "coda" package (Plummer et al., 2006) for R (R Core Team, 2014); and we report JZS BF_{10} Bayes factors (Rouder et al., 2009) with standard priors (i.e., with a scaling factor of 0.707), calculated using the BayesFactor package (Morey, Rouder & Jamil, 2014) for R, for hypothesis-guided t-tests.

Results

To examine for carry-over of probability learning effects from day 1 to day 2, and specifically differential carry-over effects between the same- and different-dimension distractor groups, we assessed (i) the (successful) establishment of the probability-cueing effect for both same- and different-dimension distractors in the learning phase, (ii) the 'peak' probability cueing effect in the last block of the learning phase, and (ii) whether or not there was still an area bias (i.e., probability-cueing effect) during early blocks of the second session (despite the fact that the distractor distribution was now equal between the previously frequent and rare areas).

The results are illustrated in Figure 2 for the two sessions (panel A, learning session; panel B, test session); each panel presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension vs. different-dimension).

Prior to more hypothesis-driven analysis (using t-tests; see below), we examined the RT data by means of a repeated-measures ANOVAs with the factors distractor condition (frequent vs. rare vs. absent), target position (frequent distractor region vs. rare distractor region), and session (training vs. test), separately for same- and different-dimension distractors. For same-dimension distractors, the ANOVA revealed all main effects to be significant: distractor condition ($F(2, 44) = 116.34$, $p < .001$, $\eta_p^2 = .84$), indicative of significant distractor interference, and differential interference dependent on the region in which the distractor occurred; target position ($F(1, 22) = 5.69$, $p = .026$, $\eta_p^2 = 0.21$), due to slower RTs to targets in the frequent as compared to the rare distractor region; and session ($F(1, 22) = 51.24$, p

$< .001$, $\eta_p^2 = 0.7$), reflecting faster responding in session 2 than in session 1. Furthermore, the following interactions were significant: distractor condition × target position ($F(2, 44) = 10.24$, $p < .001$, $\eta_p^2 = 0.32$); distractor condition × session ($F(2, 44) = 81.79$, $p < .001$, $\eta_p^2 = 0.7$), with reduced distractor interference (and equivalent interference between the two distractor regions) in session 2 than in session 1; target position × session ($F(1, 22) = 42.91$, $p < .001$, $\eta_p^2 = 0.66$), reflecting a target position effect in session 1, but not (i.e., no longer) in session 2; and (the three-way interaction) distractor condition × target position × session ($F(2, 44) = 8.87$, $p = .001$, $\eta_p^2 = 0.29$).

For different-dimension distractors, there were also significant main effects of distractor condition ($F(2, 46) = 73.18$, $p < .001$, $\eta_p^2= 0.76$) and session ($F(1, 23) = 14.14$, $p = .001$, $\eta_p^2 = 0.38$), the distractor condition × session was significant ($F(2, 46) = 18.11$, $p < .001$, $\eta_p^2 = 0.44$) as well as the interaction distractor condition × target position ($F(2, 46) = 8.42$, $p = .001$, $\eta_p^2 = 0.27$). Crucially, however, there were no other reliable effects involving target position (main effect: $F(1, 23) = 0$, $p = .947$, $\eta_p^2 = 0$; interaction target position × session: $F(1, 23) = 0.18$, $p = .672$, $\eta_p^2 = 0.01$; three-way interaction distractor condition × target position × session: $F(2, 46) = 0.94$, $p = .4$, $\eta_p^2 = 0.04$).

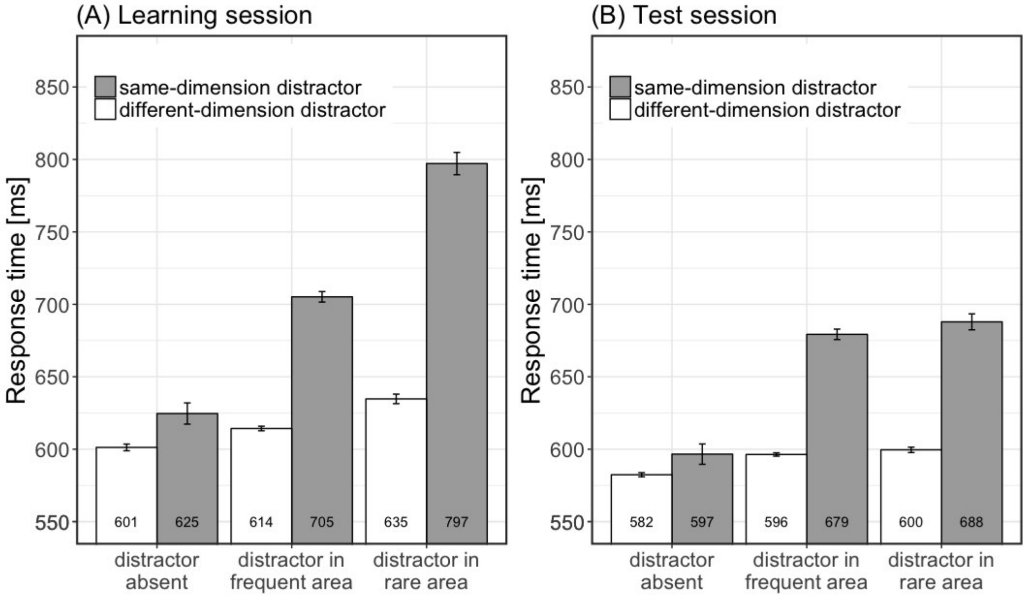

Figure 2. Reaction times as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension in gray vs. different-dimension in white) for both the learning session (A) and the test session (B) of Experiment 1.

Effects in the learning session: establishing the probability-cueing effect.

To ascertain that distractors caused interference and a probability-cueing effect was successfully established, we first examined for this effect pattern for the learning session (in which there was a 90/10 distribution). Also, we examined for the presence (same-dimension condition) versus absence (different-dimension condition) of a target position effect.

Same-dimension distractors. Same-dimension distractors caused considerable interference: RTs were 92 ms slower when a distractor was present (averaged across trials with distractors in the frequent and rare regions) versus absent (717 ms vs. 625 ms; $t(22) = 10.6, p < .001, d_z = 2.21$, 95% HPD [71 ms, 108 ms], $BF_{10} = 50 \times 10^6$. In addition, there was a large probability-cueing effect: RTs were 90 ms faster when a distractor was presented in the frequent area compared to the rare area (707 ms vs. 797 ms; $t(22) = -10.83$, $p < .001$, $d_z = 2.26$, 95% HPD [-107 ms, -72 ms], $BF_{10} = 7.379 \times 10^7$). In line with this, distractor interference (relative to the distractor-absent baseline) was reduced for distractors in the frequent rare area (81 ms; t(22) = 10.18, p < .001, d_z = 2.12, 95% HPD [64 ms, 96 ms], BF_{10} = 1.25 × 10^7) compared to distractors in the rare area (171 ms; t(22) = 13.02, p < .001, d_z = 2.71, 95% HPD [140 ms, 198 ms], BF_{10} = 1.012 × 10^9). Additionally, there was a significant target location effect: targets were responded to slower in the frequent distractor region compared to the rare region (687 ms vs. 646 ms; t(22) = 3.39, p = .001, d_z = 0.71, 95% HPD [13 ms, 61 ms], BF_{10} = 30).[26]

The same pattern was evident in the last block of the training session, – which, arguably, provides the most appropriate reference condition for examining for a carry-over effect to the test session (see below). RTs were 189 ms faster when a distractor was present in the frequent compared to the rare area (664 ms vs. 853 ms; t(22) = -3.46, p = .001, d_z = 0.72, 95% HPD [-289 ms, -65 ms], BF_{10} = 35), and distractor interference was greatly reduced (though still significant) for distractors in the frequent rare area (55 ms; t(22) = 6, p < .001, dz = 1.25, 95% HPD [35 ms, 72 ms], BF_{10} = 4224) compared to distractors in the rare area (244 ms; t(22) = 4.2, p < .001, d_z = 0.88, 95% HPD [112 ms, 337 ms], BF_{10} = 86). Moreover, targets were responded to slower in the frequent distractor region compared to the rare region (656 ms vs. 618 ms; t(22) = 3.43, p = .001, d_z = 0.72, 95% HPD [12 ms, 56 ms], BF_{10} = 33).

Different-dimension distractors. Different-dimensions distractors, too, caused general interference: RTs were slightly, but significantly, slower overall on

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[26] Note that the target-location effect reported here is the 'raw' effect, uncorrected for positional intertrial and target-to-distractor distance effects (see Supplement in Sauter et al., 2018, for details). Importantly, Sauter et al. (2018) showed that, in the same-dimension condition, the target location effect survives the various corrections that may be considered necessary for estimating the 'pure' effect. Applying these corrections to the present, limited data set (which were part of the larger set examined by Sauter et al., 2018; see footnote 7) is not feasible as this would involve the loss of too many data points for the condition with a distractor appearing in the rare region. For the present purposes, it is sufficient to note that there is a significant (raw) target location effect in the same-dimension distractor condition, but no evidence of such an effect in the different-dimension distractor condition – replicating, in this subsample, the pattern that Sauter et al. (2018) established for the complete data set.

distractor-present compared to distractor-absent trials (617 ms vs. 602 ms; t(23) = 6.67, p < .001, d_z = 1.36, 95% HPD [9 ms, 19 ms], BF_{10} = 42240). Further, different-dimension distractors too led to location probability learning: RTs were faster when a distractor appeared in the frequent as compared to the rare area (615 ms vs. 636 ms; t(23) = -4.94, p < .001, dz = 1.01, 95% HPD [-30 ms, -12 ms], BF_{10} = 930 – though, again, this effect (of 21 ms) was much smaller than that with same-dimension distractors (90 ms). Accordingly, the net distractor interference (with reference to the distractor-absent baseline) was reduced for distractors in the frequent area (13 ms; t(23) = 6.21, p < .001, d_z = 1.27, 95% HPD [8 ms, 16 ms], BF_{10} = 7802) compared to distractors in the rare area (34 ms; t(23) = 6.64, p < .001, d_z = 1.36, 95% HPD [21 ms, 43 ms], BF_{10} = 19880). Additionally, in contrast to the same-dimension condition, there was no target location effect; rather, with different-dimension distractors, targets were responded to equally fast in the frequent and the rare distractor region (612 ms vs. 610 ms; t(23) = 0.23, p = .409, d_z = 0.05, 95% HPD [0 ms, 16 ms], BF_{10}= 0.2583).

A similar pattern was also evident by the end (in the last block) of the training session. RTs were 32 ms faster when a distractor was present in the frequent area compared to the rare area (596 ms vs. 630 ms; t(23) = -3.22, p = .002, d_z = 0.66, 95% HPD [-52 ms, -10 ms], BF_{10} = 22). And while distractor interference (relative to the distractor-absent baseline) had been effectively abolished for distractors in the frequent area (4 ms; t(23) = 0.63, p = .534, d_z = 0.13, 95% HPD [-9 ms, 15 ms], BF_{10} = 0.26), interference remained significant for distractors in the rare area (38 ms; t(23) = 2.96, p = .007, d_z = 0.6, 95% HPD [11 ms, 60 ms], BF_{10} = 7). There was also no target location effect: RTs were equally fast to targets in the frequent and rare distractor areas (596 ms vs. 593 ms; t(23) = 0.44, p = .333, d_z = 0.09, 95% HPD [0 ms, 15 ms], BF_{10} = 0.31)

We thus established that both types of distractors generated the crucial, expected probability-cuing effect in the learning session, with a larger effect for same-compared to different-dimension distractors. Additionally, distractor location probability cueing was associated with a marked target location effect in the same-dimension distractor condition, but the absence of such an effect in the different-dimension condition. Note that this is a complete replication of the findings of Sauter et al. (2018).

Distractor interference in the test session: is there carry-over of probability cueing from the learning to the test session?

Recall that the probability distribution in the test session was changed (from uneven, 90/10, in the learning session) to even (50/50) for the two distractor regions. Thus, given that the previously frequent and the previously rare area were now equally likely to contain a distractor, there would no longer be a benefit in suppressing one half of the display more than the other. Also, there cannot be any renewed learning of the previous, uneven distribution, which might instead be unlearned based on the sampling of the now even distribution. Thus, given the likelihood of unlearning (brought about by the changed, even distribution), we examined for carry-over by comparing performance between the last block of trials in the learning session, which can be taken to reflect maximum learning (see results above), with the first block in the test session (performed at least 24 hours after the last block of the training session!), which involves minimum unlearning. See Figure 3 for a depiction of the RT data (last block of learning session and first block of test session).

Same-dimension distractors. In the first block of the test session, a probability-cueing effect was still evident: RTs were still faster, by 29 ms, when a distractor was presented in the (previously) frequent area compared to the (previously) rare area (728 ms vs. 757 ms; t(22) = -2.63, p = .008, d_z = 0.55, 95% HPD [-46 ms, -6 ms], BF_{10} = 6.761). This goes along with the net distractor interference effect (with reference to the distractor-absent baseline) being still smaller for distractors in the frequent area (109 ms; t(22) = 8.45, $p < .001$, $d_z = 1.76$, 95% HPD [79 ms, 131 ms], $BF_{10} = 5.723 \times 10^5$) compared to distractors in the rare area (138 ms; t(22) = 10.45, $p < .001$, $d_z = 2.18$, 95% HPD [108 ms, 165 ms], $BF_{10} = 1.978 \times 10^7$). There was also a small numerical, though non-significant target-location effect (676 vs. 665 ms; t(22) = 0.86, p = .200, $d_z = 0.18$, 95% HPD [0 ms, 31 ms], $BF_{10} = 0.4803$).

Different-dimension distractors. The probability-cueing effect was no longer significant in the first block of the test session, that is, there was no longer an RT advantage for distractors appearing in the (previously) frequent versus the (previously) rare area (607 ms vs. 615 ms; t(23) = -1.2, p = .12, $d_z = 0.25$, 95% HPD [-19 ms, 0 ms], $BF_{10} = 0.71$). This also means that the (significant) net distractor interference effects were comparable between distractors in the frequent area (27 ms; t(23) = 4.53, $p < .001$, $d_z = 0.92$, 95% HPD [14 ms, 38 ms], $BF_{10} = 187$) and distractors in the rare area (35 ms; t(23) = 5.2, $p < .001$, $d_z = 1.06$, 95% HPD [20 ms, 47 ms], $BF_{10} = 833$).

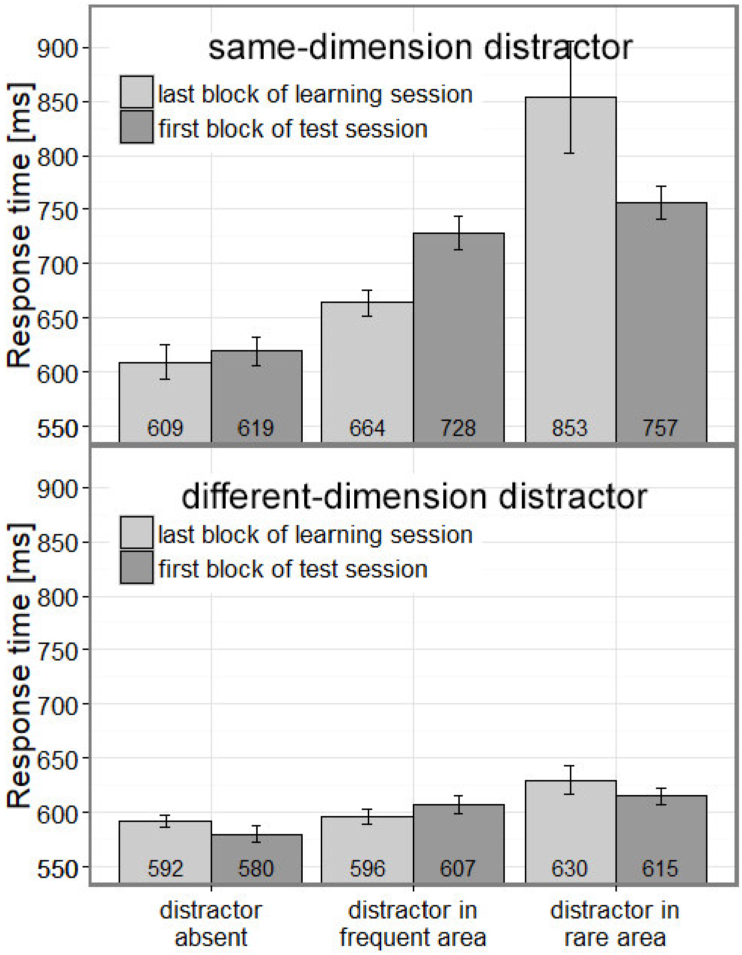
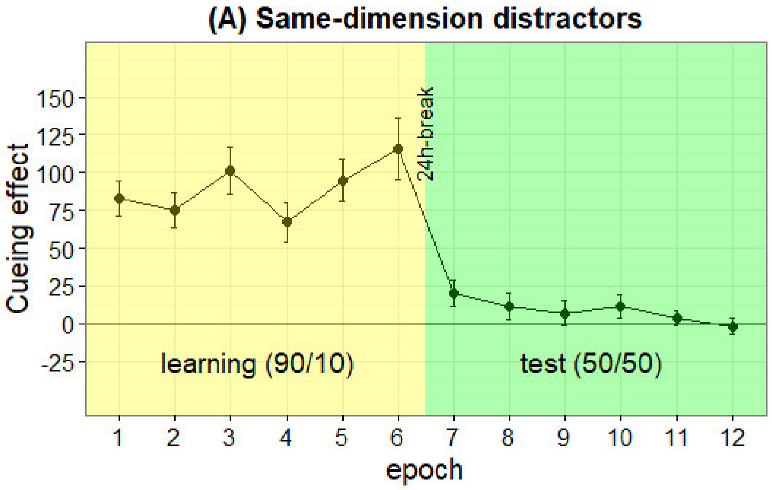
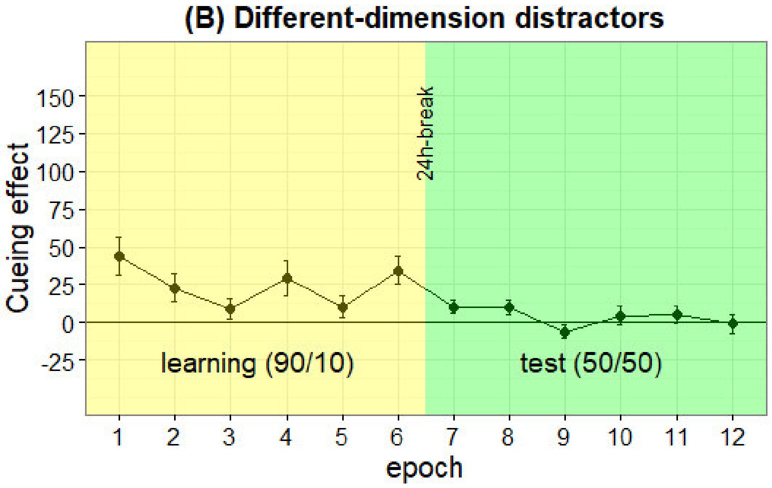


Figure 3. Reaction times as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) and the first block of the test session (dark gray) for same-dimension (top panel) and different-dimension distractors (bottom panel).

Distractor location probability cueing: learning and unlearning.

Figure 4 depicts the development of distractor probability cueing over time in the training (learning) and the test sessions (unlearning/re-learning); that is, the probability-cueing effect (RT difference with distractors in rare minus frequent area) is depicted as a function of experimental 'epoch', where an epoch summarizes the effect across two consecutive trial blocks, to smooth a more noisy, block-wise developmental pattern. As can be seen, learning occurs quite rapidly – essentially within the first epoch – with both same- and different-dimension distractors.[27] Concerning unlearning, residual effects of the uneven distribution (during learning) appears to reduce gradually, over the course of four to five epochs (960 to 1200 trials) with the even distribution, with same-dimension distractors. With different-dimension distractors, by contrast, unlearning of the old, uneven distribution appears to happen relatively quickly: within one epoch (240 trials) the most (recall that there was no significant carry-over effect into the first block of the test session, suggesting that adaptation to the new, even distribution occurs within 120 trials).


(A) Same-dimension distractors


(B) Different-dimension distractors

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[27] Distractor position (frequent, rare region) x epoch ANOVAs failed to reveal the interaction to be significant, both with same-dimension distractors, $F(5, 105) = 1.77$, $p = .125$, $\eta_p^2 = 0.08$, and with different-dimension distractors $F(5, 115) = 2.02$, $p = .081$, $\eta_p^2 = 0.08$.

Figure 4. Development of the probability cueing effect over the learning session (yellow; uneven, 90/10, distractor distribution) and test session (green; even, 50/50, distractor distribution) for same- (A) and different dimension (B) distractors. Error bars indicate within-subject SEM (Morey, 2008).

Discussion

Taken together, Experiment 1 replicated the findings of Sauter et al. (2018), confirming differential distractor location probability-cueing effects between same- and different dimension distractors. With both types of distractor, though, the learning of the spatial distractor distribution occurred rather rapidly, within the first few hundred (if not tens) of trials, yielding only minor, if any, increases in the cueing effect beyond the first epoch. This finding of rapid spatial learning is in line with other studies, such as Ferrante et al. (2018; see also Jiang, Swallow, Rosenbaum, & Herzig, 2013), that used much sparser displays and specific locations (e.g., four-item displays with a single likely distractor location) rather than probability cueing of larger display regions.

Our main goal, however, was to test how persistent these learning effects would be when distractors in the second (test) session are equally likely to appear in the previously frequent and the previously rare display region (i.e., after the removal of the biased distractor distribution) and whether this would differ between the two types of distractors. In agreement with Ferrante et al. (2018) – who used a shape-defined target singleton and a color-defined distractor singleton – Experiment 1 revealed near-instant 'extinction' of the learnt distractor location cueing effect with different-dimension distractors (orientation-defined target, color-defined distractor).

For same-dimension distractors[28], by contrast, the probability-cueing effect was still evident (significant) in the second session (i.e., 24 hours plus after initial learning) indicating relatively robust long-term learning of the likely distractor locations. This effect was, however, significantly reduced relative to the last block of the training session, likely owing to the time elapsed as well as (potentially rapid) 'unlearning' of the old distractor distribution. Nevertheless, residual effects of the induced probability-cueing effect remained for (at least) one epoch of some 400 trials, indicating that some training is needed to successfully adapt to (i.e., re-learn) the new distribution for same-dimension distractors.

The differential carry-over effect with same- versus different-dimension distractors is in line with our hypothesis: deeper learning with different-dimension distractors, which distract more and thus involve increased recruitment of cognitive control to mitigate the interference they cause (Liesefeld et al., 2017). That is, there is a greater incentive to retain the learnt suppression routines, which then still tend to be retrieved (invoked by aspects of the search displays) even if the learnt distractor distribution does not apply any longer (in Experiment 1: in the test session), and unlearning takes several 100 (400+) trials to adapt to the even distribution. Different-dimension distractors, by contrast, are easier to deal with, as effective routines (such as dimension-based suppression) are more readily available. Accordingly, there is a reduced need for long-term retention and/or fast, effectively instantaneous, adaptation to the changed distribution.

Experiment 2

In Experiment 1, carry-over of probability cueing from the learning and to the test session, conducted after a gap of at least 24 hours, was observed only with same-

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[28] Note that Ferrante et al. (2018) did not examine a same-dimension distractor condition, so their findings tell us nothing about unlearning in this condition.

dimension distractors in both sessions, but not with different-dimension distractors. The latter result leaves it open whether, with different-dimension distractors, forgetting of the initially learnt, unequal distractor distribution occurred more or less immediately or whether it took a longer delay (of up to 24-plus hours) for between initial learning and test for forgetting to manifest. Experiment 1 was designed to examine this by running the learning and test phases consecutively on one and the same day, with only a 5-minute break in between. The question, thus, was whether, with the immediate change (from the uneven distribution during learning) to the even distribution during test, there would be discernible carry-over of the initially learnt distribution for some time (i.e., experimental blocks or epochs) before the cueing effect is effectively abolished by the acquisition of the new distribution, and for how many epochs such a carry-over effect could be demonstrated. Accordingly, Experiment 2 focused on the different-dimension (distractor) condition. However, in order to establish any differences unlearning/relearning relative to the same-dimension condition (for which Experiment 1 had shown long-lasting and robust effects of the initial distribution, even though this was no longer reinforced by the distractor location probabilities in the test session), we also included a same-dimension condition in Experiment 2.

Methods

The design of Experiment was essentially the same as that of Experiment 1, with two exceptions. First, and most importantly, the break between the learning and test phases was only 5 minutes. Second, to make the experiment doable within one, extended experimental session, we reduced the number of blocks per session (from 12 in Experiment 1) to 4 in Experiment 2. This appeared to be justified given that learning of the uneven distractor distribution was very swift in the different-dimension condition, occurring with the maximum cueing effect achieved within two trial blocks (first epoch; see also Ferrante et al., 2018; Jiang et al., 2013).

Participants. 47 (25 female, 22 male) right-handed observers, all recruited from the LMU Munich subject pool, with a median age of 26 (range: 18–39) years, participated in Experiment 2 (24 participants with same-dimension distractors; 23 participants with different-dimension distractors). All of them reported normal or corrected-to-normal vision (including normal color vision) and gave prior informed consent. They received 8€ per hour or course credits in compensation.

Results

All analyses were analogous to those of Experiment 1. The results are illustrated in Figure 5 for the two sessions (panel A, leaning session; panel B, test session); each panel presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension vs. different-dimension).

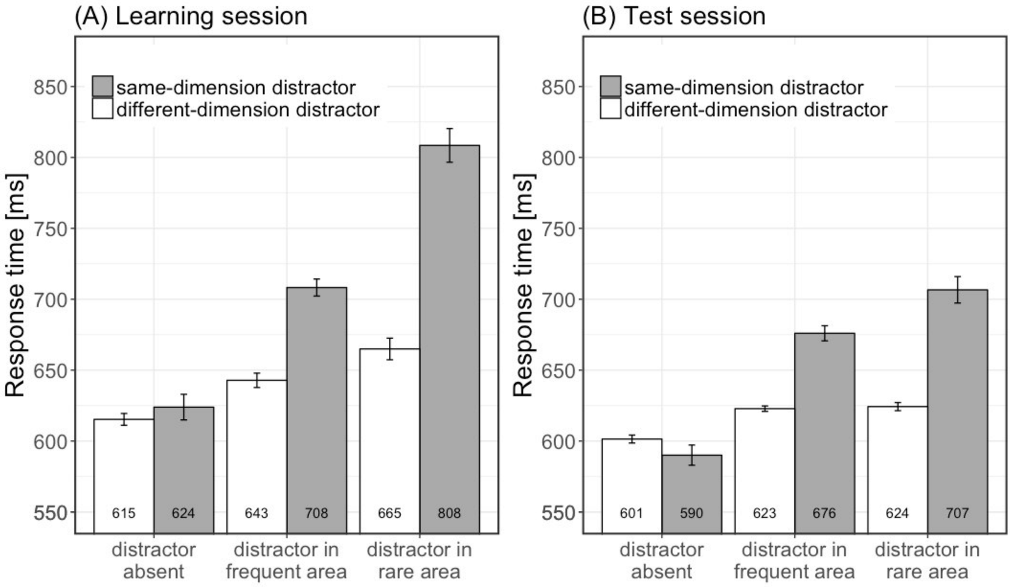

Figure 5. Reaction times as a function of the distractor condition (in frequent area vs. in rare area vs. absent) and distractor type (same-dimension in gray vs. different-dimension in white) for both the learning session (A) and the test session (B) of Experiment 2.

As can be seen from Figure 5, the results for *learning* sessions (with uneven distractor distribution) perfectly replicated those of Experiment 1: Same-dimension distractors caused more interference overall than different-dimension distractors (relative to the respective baseline: 39 ms vs. 134 ms). Also, while there was a (learnt) distractor location probability cueing effect in both distractor conditions, this effect was much more pronounced, by a factor of 5, with same-dimension relative to different-dimension distractors (same-dimension, distractor in frequent vs. rare area: 708 ms vs. 808 ms, t(23) = -6.65, p < .001, d_z = 1.36, 95% HPD [-128 ms, -65 ms], BF$_{10}$ = 40300; different-dimension: 643 vs. 665 ms, t(22) = -1.98, p = .03, d_z = 0.41, 95% HPD [-39 ms, -1 ms], BF$_{10}$ = 2.20). Note, that the net interference effect for conditions with distractors in the frequent area (relative to the baseline conditions) were reliable both for the same-dimension (84-ms interference; 84 ms; t(23) = 9.54, p < .001, d_z = 1.95, 95% HPD [65 ms, 102 ms], BF$_{10}$ = 6.254×10^6) and for the different-dimension condition (28-ms interference; t(22) = 5.74, p < .001, d_z = 1.2, 95% HPD [16 ms, 37 ms], BF$_{10}$ = 2410). Finally, there was a differential target position effect between the two distractor conditions: for same-dimension distractors, responses were slower to targets that appeared in the frequent distractor area compared to targets in the rare area (70-ms difference: 704 ms vs. 634 ms, t(23) = 3.8, p < .001, d_z = 0.78, 95% HPD [26 ms, 100 ms], BF$_{10}$ = 76), whereas there was no such effect with different-dimension distractors (–1-ms difference: 629 ms vs. 630 ms, t(22) = -0.07, p = .526, d_z = 0.01, 95% HPD [0 ms, 23 ms], BF$_{10}$ = 0.208).

For the *test sessions* (with even distractor distributions), the results also turned out very similar to Experiment 1. Differential interference from distractors in the (previously) frequent versus the rare region was still evident for the same-dimension distractor condition (676 ms vs. 707 ms, t(23) = -2.50, p = .010, d_z = 0.51, 95% HPD [-51 ms, -5 ms], BF$_{10}$ = 5.39), but being completely abolished for the different-dimension distractor condition (623 ms vs. 624 ms, t(22) = -0.4, p = .347, d_z = 0.08, 95% HPD [-8 ms, -0 ms], BF$_{10}$ = 0.304). In other words, there was carry-over of the learnt distractor distribution from the learning to the test session in the same-dimension condition (despite the fact that both regions were equally likely to contain a distractor in the test session), but no carry-over in the different-dimension condition. Also, there remained a robust target location effect (with slower RTs to targets in the previously frequent vs. the rare distractor area) in the same-dimension: 36-ms difference (653 ms vs. 617 ms, t(23) = 2.26, p = .017, d_z = 0.46, 95% HPD [4 ms, 62 ms], BF_{10} = 3.47), which compares with a 70-ms difference in the learning session. In the different-dimension condition, by contrast there was no such effect (–13-ms difference, 606 ms vs. 619 ms, t(22) = -1.21, p = .88, d_z = 0.25, 95% HPD [0 ms, 16 ms], BF_{10} = 0.11); recall that there was also no target location effect in the learning session (–1-ms difference). This differential pattern indicates that not only the distractor location effect was carried over from the learning to the test session in the same-dimension condition, but also, coupled with this, the target position effect. (As there was no target position effect in the learning session of the different-dimension condition, no such effect could be carried over to the test session.)

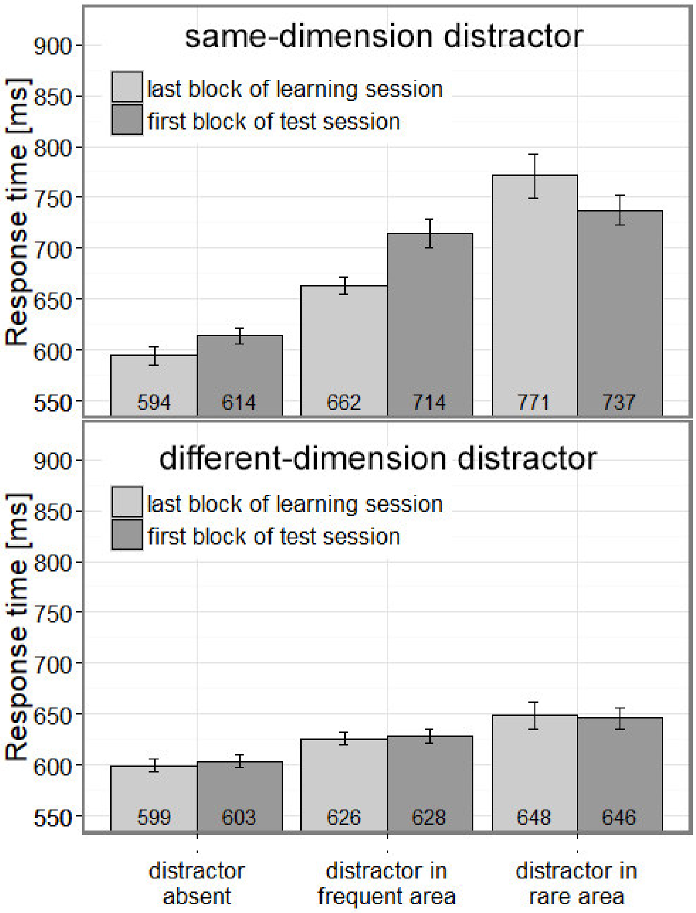

Figure 6. Reaction times as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) and the first block of the test session (dark gray) for same-dimension (top panel) and different-dimension distractors (bottom panel).

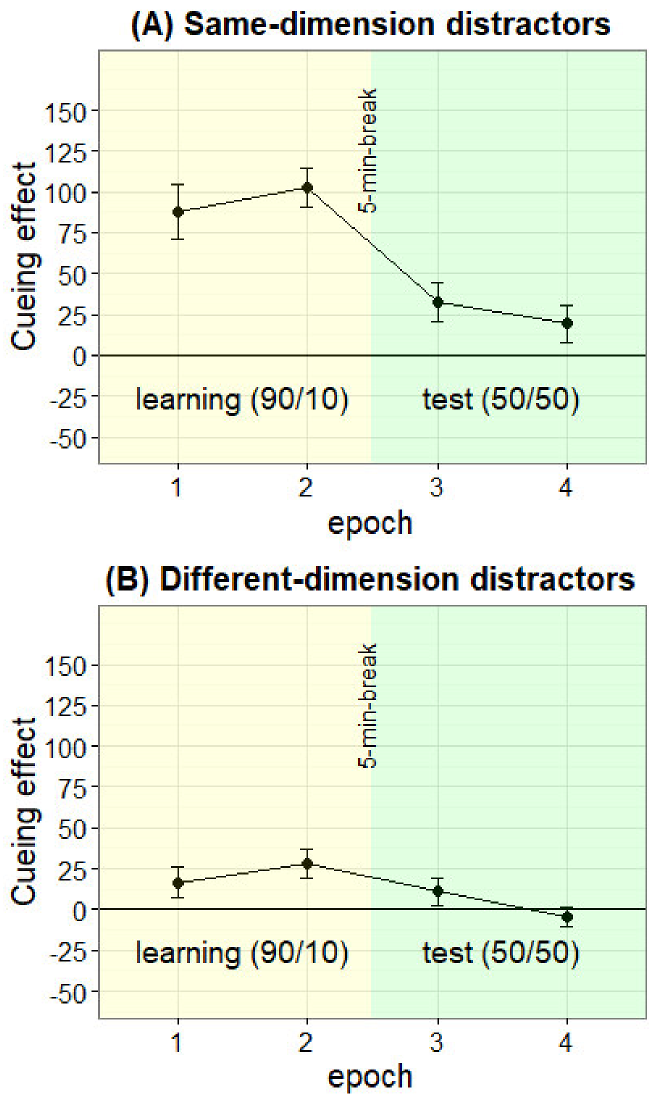

Figure 7. Development of the probability cueing effect over the learning session (yellow; 90/10 distribution) and test session (green; 50/50 distribution) for same- (A) and different dimension (B) distractors. Error bars indicate within-subject SEM (Morey, 2008).

Looking at the carry-over effects in an epoch-wise manner (see Figure 7; see also Figure 6 for a depiction of the carry-over effects between the last block of the learning session and the first block of the test session), it appears that there was relatively little unlearning of the initially acquired distractor distribution over time (i.e., experience with the even distribution) in the test session with the same-dimension condition: The carry-over effects were 33 and 19 ms in the first and the second epoch of the test session, respectively (first epoch: 690 ms vs. 723 ms; t(23)

= -2.66, p = .007, d_z = 0.54, 95% HPD [-53 ms, -7 ms], BF_{10} = 7.315; second epoch, 670 ms vs. 690 ms; t(23) = -1.48, p = .076, d_z = 0.3, 95% HPD [-39 ms, -0 ms], BF_{10} = 1.023).

In the different-dimension condition, there was a numerical, but non-significant, probability cueing effect, of 11 ms, in the first epoch of the test session (621 ms vs. 632 ms; t(22) = -1.65, p = .057, d_z = 0.34, 95% HPD [-21 ms, 0 ms], BF_{10} = 1.317), and there was no evidence of any effect for the second epoch (626 ms vs. 622 ms; t(22) = 1.05, p = .848, d_z = 0.22, 95% HPD [-6 ms, 0 ms], BF_{10} = 0.12).

Discussion

Thus, overall, Experiment 2 essentially replicates Experiment 1 in virtually all respects. That is, even with an immediate switch from the learning (uneven distractor distribution) to the test session (even distribution), there is a significant carry-over effect of the learnt distractor distribution (along with the associated target location effect) only for the same-dimension condition, but not for the different dimension condition. In the latter, the mechanisms underlying the distractor suppression adapt more or less immediately to the changed distractor statistics. By contrast, although there is an element of unlearning (instigated by the changed distractor distribution) in the same-dimension condition (the distractor location effect is overall weaker in the test session compared to the learning session, and there is some evidence of a decrease in the effect across blocks in the former session), it is safe to conclude that it takes several hundred trials of exposure to the new distribution for the distractor location cueing effect to be completely abolished. Across the whole test session in the same-dimension-condition, the cueing effect remained at 31 ms, which compares with ~20 ms for blocks 1 to 4 in Experiment 1, in which the test session was conducted at least 24 hours after the learning session. This suggests that there is actually very little forgetting as a function of the time between learning and test (at least within a one-day period), and ‘forgetting’ is largely attributable to unlearning by exposure to the new statistical distractor distribution. The fact that the initially acquired cueing effect is less robust in face of the changed distribution (i.e., the effect dissipates much more rapidly) in the different-dimension distractor condition provides further evidence that the underlying mechanism is (qualitatively) different from that in the same-dimension condition.

Experiment 3

In Experiments 1 and 2, carry-over of probability cueing from the learning and to the test session was observed only with same-dimension distractors, but not with different-dimension distractors. Experiment 3 was similar in design to Experiment 1 (with a 24-plus hour gap between the learning and the test sessions), but it examined for a new carry-over effect: participants were presented with same-dimension distractors in the learning session (90/10 distribution), followed by a switch to different-dimension distractors in the test session (50/50 distribution). That is, the question was: would there also be carry-over of distractor location probability learning from same- to different-dimension distractors? As outlined in the Introduction, the answer has implications for the locus of the probability-cueing effect in the same-dimension condition. Assuming that what is learnt in the same-dimension condition is dimension-based suppression (i.e., stronger suppression of any orientation contrast signals in the frequent vs. the rare distractor region), we would not expect a carry-over of probability cueing from same-dimension (i.e., orientation-defined) distractors at learning to different-dimension (i.e., color-defined) distractors at test. Concretely, if participants learn to down-weight orientation signals (more so signals in the frequent compared to the rare distractor area) in the learning session, this learnt weight set should not modulate the weighting of distractors defined in a different, namely, the color dimension in the test session (because participants did not learn to down-weight color signals). By contrast, carry-over would be expected if, with same-dimension distractors at learning, participants develop a strategy of space-based suppression (stronger for the frequent vs. the rare region) operating at the level of the search-guiding master saliency map. That is, if, with same-dimension distractors, participants learn to (strongly) suppress any master map signal (in the frequent distractor area), this suppressive set – which Experiment 1 revealed is carried over to (at least the first block of) the test session – should (after the switch) also apply to signals originating from a different dimension. The reason is that, due to the summing of feature contrast signals across dimensions, overall-saliency coding is 'feature-less' or 'feature-blind': saliency signals only indicate that there is an object at a particular location that differs (to a certain degree) from the objects in its surround, but they do not indicate what constitutes the difference; for instance, whether it is a color difference (rather than an orientation difference) and, if so, whether the odd-one-out feature is 'red' (rather than grey). Thus, carry-over of distractor probability cueing from same-dimension to different-dimension distractors would manifest only if the locus of the learning is the overall-saliency map (rather than learning being implemented at a dimension-specific level).

Methods

Participants. 24 observers (9 female, 15 male; all right-handed; all with normal or corrected-to-normal vision, including normal color vision; median age 28, range: 21–39, years) participated in this experiment. All of them gave prior informed consent, and received 8€ per hour for their service.

Apparatus, design, stimuli and procedure. The apparatus, the stimuli, and the design and procedure were exactly the same as in Experiment 1. The only difference to

Experiment 1 was that distractors were consistently orientation-defined in the first, learning session (*horizontal* [gray] bar, differing from the vertical [gray] non-targets in the same dimension as the – 12° tilted [gray] – target bar), and consistently color-defined in the test session (*red* [vertical] bar, differing from the gray [vertical] non-targets in a different dimension to the [gray] 12° tilted target bar).

Results

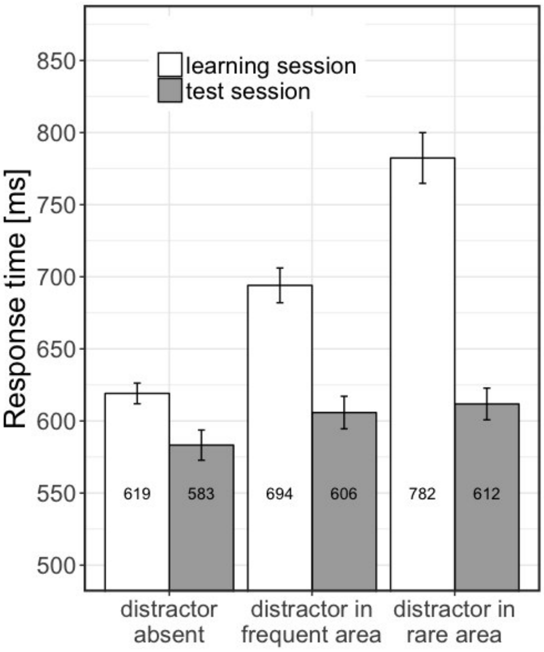

Figure 8. Reaction times as a function of the distractor condition (in frequent area vs. in rare area vs. absent) for both the learning session with same-dimension distractors, and the test session with different dimension distractors. Error bars indicate the within-subject standard error of the mean (Morey, 2008).

Figure 8 presents the median correct RTs as a function of the distractor condition (in frequent area vs. in rare area vs. absent), for the learning session with same-dimension distractors and for the test session with different-dimension distractors. In the *learning* session, as in (the same-dimension condition of) Experiment 1, there is both distractor interference (i.e., slower RTs on distractor-present vs. distractor-absent trials) and probability cueing (i.e., relatively faster RTs, and less interference, with a distractor in the frequent vs. a distractor in the rare region). In the *test session*, there too is evidence of distractor interference (reduced relative to the learning session, owing to the switch from same- to different-dimension distractors); however, across the whole test session, there is scant evidence of any distractor location probability-cueing effect. [These differential effects were confirmed by an RT ANOVA, with the factors distractor condition (in frequent area vs. in rare area vs. absent) and session (learning vs. test), which, besides the two main effects, revealed the interaction to be significant: distractor condition, F(2, 46) = 111.68, $p < .001$, $\eta_p^2 = 0.83$; session, F(1, 23) = 25.31, $p < .001$, $\eta_p^2 = 0.52$; interaction, F(2, 46) = 70.86, $p < .001$, $\eta_p^2 = 0.75$.] Given the possibility of relatively rapid unlearning of the previous distractor distribution (after the change from a 90/10 to a 50/50 distribution) and given the overall reduced interference with different-dimension distractors, carry-over effects would be expected to be obtained only (if at all) early during the test session. Given this, following the confirmation of distractor interference and the establishment of probability cueing in the learning session, a more detailed examination of the test session will focus on the first block(s) only.

Distractor interference in the training session. A comparison of RTs on distractor-present trials versus those on distractor-absent trials revealed significant distractor interference: RTs were 83 ms slower overall when a distractor was present rather than absent (702 ms vs. 619 ms; t(23) = 9.08, $p < .001$, $d_z = 1.85$, 95% HPD [62 ms, 101 ms], $BF_{10} = 5.36 \times 10^6$). Furthermore, the probability-cueing effect was significant: RTs were 88 ms faster when a distractor was presented in the frequent area as compared to the rare area (707 ms vs. 794 ms; t(20) = -7.6, $p < .001$, $d_z = 1.66$, 95% HPD [-109 ms, -60 ms], $BF_{10} = 1.258 \times 10^5$). Given the same distractor-absent baseline, this also means that distractor interference in the frequent area (75 ms; t(20) = 7.49, $p < .001$, $d_z = 1.63$, 95% HPD [50 ms, 93 ms], $BF_{10} = 51430$) caused less interference than distractors in the rare area (162 ms; t(20) = 9.51, p < .001, d_z = 2.07, 95% HPD [126 ms, 193 ms], $BF_{10} = 1.679 \times 10^6$). Additionally, there was a significant target location effect, with targets being responded to slower in the frequent than in the rare region (668 ms vs. 645 ms; t(23) = 2.79, p = .005, d_z = 0.57, 95% HPD [5 ms, 38 ms], BF_{10} = 9.28).

Distractor interference in the test session. To examine whether traces of the probability-cueing effect established in the learning session would still be left after the change of the probability distribution (from 90/10 to 50/50) and the type of distractor (from same- to different dimension) in the test session, we focused our analysis on the first block of the second session. See Figure 9, which depicts the transition between the last block of the learning session (same-dimension distractors, 90/10 distribution) and the first block of test session (different-dimesnion distractors, 50/50 distribution). Again, (different-dimension) distractors were found to generally cause interference: RTs were overall slower, by 47 ms, when a distractor was present as compared to absent (663 ms vs. 616 ms; t(23) = 7.2, p < .001, d_z = 1.47, 95% HPD [32 ms, 59 ms], $BF_{10} = 1.3 \times 10^5$). In addition, there was still a significant probability-cueing effect: RTs were still faster, by 17 ms (654 ms vs. 671 ms; t(23) = -2.00, p = .029, d_z = 0.41, 95% HPD [-29 ms, 0 ms], BF_{10} = 2.265)[29], and distractor interference (relative to the distractor-absent baseline) remained reduced, when a distractor was presented in the frequent area compared to the rare area (net interference frequent area: 38 ms; t(23) = 5.54, p < .001, d_z = 1.13, 95% HPD [23 ms, 54 ms], BF_{10}= 1.80; net interference rare area: 55 ms; t(23) = 7.15, p < .001, d_z = 1.46, 95% HPD [37 ms, 69 ms], BF_{10} = 59). Additionally, there was a significant target-location effect, 650 ms vs. 626 ms (t(23) = 1.73, p = .048, d_z = 0.35,

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[29] In case the Bayes factor, BF_{10} = 2.265, might not be considered convincing, we calculated the critical probability- cueing effect across all 12 blocks of the test session (instead of only the first block). Including all blocks is conservative with regard to our hypothesis, because the acquired spatial suppression is unlearned over trials. Still, RTs were significantly faster with distractors appearing in the frequent compared to the rare distractor area (606 ms vs. 612 ms; t(23) = -3.4, p = .001, d_z = 0.69, 95% HPD [-9 ms, -2 ms], BF_{10} = 32).

95% HPD [0 ms, 44 ms], BF_{10} = 1.48), though not entirely convincing under Bayesian scrutiny.[30]

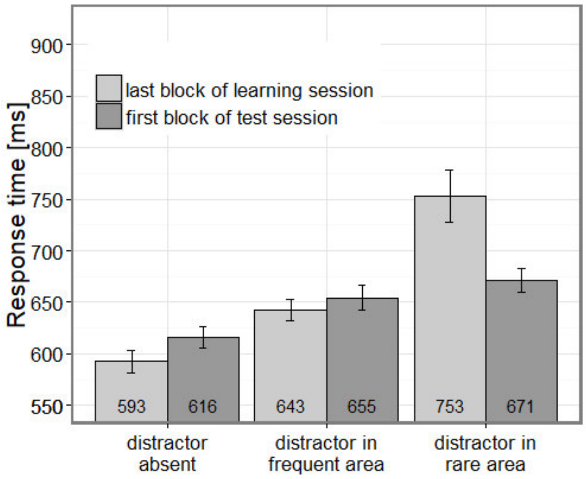

Figure 9. Reaction times as a function of the distractor condition (absent vs. frequent area vs. rare area) for the last block of the learning session (light gray) with same-dimension distractors and the first block of the test session (dark gray) with different-dimension distractors.

Discussion

Thus, Experiment 3 demonstrates that a probability-cueing effect established with same-dimension distractors in the learning session does carry over (after 24 plus hours) to the test session with different-dimension distractors. This was the case even though distractors were equally likely to occur in each of the previously frequent and rare regions on the second day, that is, observers could not have learned the uneven distribution anew with different-dimension distractors. We take this to mean that a special space-based suppression strategy developed to deal with same-dimension distractors (namely: suppression of the frequent area at the level of the master map) continues (at least initially) to be applied even to different-

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[30] With the changed (i.e., different-dimension) distractor during the test session as well as the even distractor distribution, unlearning of the cueing effect (acquired with same-dimension distractors) occurred then quite rapidly: a probability cueing effect, or target location effect, was no longer discernible statistically from the second block onwards.

dimension distractors, even though the latter can, and would, normally be dealt with using a dimension-based suppression strategy.

General Discussion

The present results show that a distractor location probability-cueing effect developed during a learning session carries over to a test session (even when the latter is conducted some 24 hours after the learning session) only with same-dimension distractors, but not with different-dimension distractors (Experiments 1 and 2). Only for same-dimension distractors, distractor interference in the test session remained reduced for the (previously) frequent distractor area, compared to the (previously) rare distractor area, even though distractors were distributed evenly in the test session – affording no opportunity for re-learning of the previous (uneven) distribution. However, even with same-dimension distractors, the effect was reduced in the first block of the test session compared to the last block of the training session, indicative of relatively fast unlearning of the old (and new learning of the changed) distribution, though it took some 880 plus trials (i.e., 4 plus epochs) of practice with the changed distribution for the effect to be completely unlearnt (see Figure 4). We take this overall-pattern to indicate that practice with an uneven distribution of same-dimension distractors (which cause a greater degree of conflict) yields deeper – and thus better consolidated and persistent – probability learning effect than practice with different-dimension distractors.

Given the differential manifestation of target-location effects between same- and different-dimension distractors (only the former, but not the latter, were associated with slowed responding to targets in the frequent as compared to the rare region; see also Sauter et al., 2018), we hypothesised that the learning is not just of differential depth, but also implemented at a different level in the hierarchical architecture of search guidance: the superordinate master map level (same-dimension distractors) as compared to the subordinate dimensional level (different-dimension distractors).

To test for this, Experiment 3 examined for carry-over of (acquired) probability cueing from learning with same-dimension distractors to test with different-dimension distractors. If, with same-dimension distractors (with which there is carry-over of leaning, as revealed by Experiments 1 and 2), the learning is implemented at the master map level, then it should generalize to a new situation with a change in the type of distractor (to a different dimension) in the test session (Hypothesis A). The reason is that, due to the summing of feature contrast signals across dimensions, overall-saliency coding is 'feature-less' or 'feature-blind': saliency signals only indicate that there is an object at a particular location that differs (to a certain degree) from the objects in its surround, without providing information about the dimension or specific feature(s) that constitute the difference (e.g., Töllner et al., 2014). Thus, if learnt suppression continues to be applied to the (previously) frequent distractor area at the level of the master map, any signal should be suppressed in this region whether it is defined in the same-dimension as the target (which was tested and confirmed in Experiment 1) or in a different dimension (which was examined in Experiment 3). Alternatively, if the learning is dimension-specific (inhibiting feature contrast signals within the distractor dimension, more strongly so in the frequent than the rare area), there should be no carry-over when the dimension of the distractor of the distractor is switched from learning to test: if one learns to specifically suppress orientation-defined distractors, one has not learnt to suppress color-defined distractors (Hypothesis B). The results of Experiment 3 are in line with Hypothesis 1: color-defined distractors continued to cause less interference in the (previously) frequent distractor area when the initial learning had occurred with same-dimension distractors (Experiment 3), but not when learning occurred with different-dimension distractors (Experiment 1).

Two further questions arise from these findings. First, why would suppression of same-dimension distractors operate at the master saliency map level, when it could, in principle, be equally implemented at the dimensional level? (Recall that the latter could also explain the target location effect with same-dimension distractors, but it fails to explain the carry-over effect from same- to different dimension distractors)? At present, only a speculative answer is possible (cf. Sauter et al., 2018): Perhaps, with same-dimension distractors, dimension-based suppression is a less viable strategy than master map suppression, as any down-weighting of the orientation dimension would conflict with the task of finding the orientation-defined target. There would thus be a goal conflict with observers, at the same time, attempting to keep any signals from the orientation dimension out of the search and selectively enhancing the target orientation. Operating suppression at the master map level would avoid such a goal conflict. Further work is required to examine the merits of this reasoning, along with answering whether the level of suppression is a strategic choice, or selected automatically based on constraints intrinsic to the stimuli.

A second question to be addressed concerns whether the account offered here (essentially a further development of the dimension-weighting account/DWA) is a general one? That is, is the present pattern of effects specific to the stimuli used in the present experiments (orientation-defined target coupled with an orientation-defined vs. color-defined distractor), or does it generalize to other dimensions of target- and distractor-defining features? While the present findings are in line with the DWA (the only general account predicting a dissociation between same- and different-dimension distractors!), further work – for instance, with luminance-, color-, and motion-defined targets and distractors defined in either the same or one of the other dimensions – is necessary for the DWA to be established as a truly general account of the asymmetry revealed in the present study. In particular, would there be a location probability cueing effect, along with a target-location effect, with all kinds of same-dimension distractors, including color distractors (for which there is good evidence of, at least a degree of, feature-based suppression)[31]? And would these effects transfer (after a distractor switch) to other (i.e., different-) distractor dimensions? Purpose-designed studies, with calibrated stimulus (saliency) settings for the various dimensions involved, are required to answer this question.

A final note concerns an intriguing pattern discernible in the transition from an uneven (last block of test session) to an even spatial distractor distribution (first block of test session), as the established distractor location probability cueing effect starts to become unlearnt: relative to the last block of learning session, RTs in first block of the test session exhibit an increase with distractors located in the frequent region and a decrease, of a similar magnitude, with distractors located in the rare region[32]. This pattern can be seen in both Experiments 1 and 2 (see Figures 3 and 6), with both types of distractor: With same-dimension distractors, RTs increased by 58 ms (collapsed across Experiments 1 and 2) when a distractor appeared in the (previously) frequent region ($t(46) = -4.83$, $p < .001$, $d_z = 0.7$, 95% HPD [-79 ms, -32 ms], $BF_{10} = 1283$) and they decreased by 65 ms when a distractor appeared in the (previously) rare region; $t(46) = 2.02$, $p = .049$, $d_z = 0.29$, 95% HPD [-1 ms, 122 ms], $BF_{10} = 1.018$). With different-dimension distractors, the pattern is qualitatively

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[31] There is good evidence that, within the color dimension, salient singletons mismatching the target color (i.e., same-dimension distractors) may fail to capture attention (contingent-capture studies: e.g., Folk, Leber, & Egeth, 2002; Lien, Ruthruff, & Cornett, 2010; Lien, Ruthruff, & Johnston, 2010; additional-singleton studies: e.g., Gaspar & McDonald, 2014; Gaspar, Christie, Prime, Jolicoeur, & McDonald, 2016). Even though there are exceptions consistent with the DWA (contingent-capture paradigm: Harris, Becker, & Remington, 2015; additional-singleton paradigm: Feldmann-Wüstefeld, Uengoer, & Schubö, 2015; Kadel, Feldmann-Wüstefeld, & Schubö, 2017), on the balance of evidence, it would appear that the suppression of color distractors does involve an element of feature-based suppression (see also Gaspelin, Leonard, & Luck, 2015, and Gaspelin & Luck, 2017). This picture is actually consistent with previous studies of dimension weighting (with combinations of color, motion, and orientation targets), in which color proved to be special: it was the only dimension producing significant feature-specific inter-trial priming and trial-wise pre-cueing effects (e.g., Found & Müller, 1996; Müller et al., 2003; Weidner, Pollmann, Müller, & von Cramon, 2002), though with dimension-based effects outweighing feature-based effects even with color targets.

[32] Given that, in addition to distractor distribution learning, there are procedural learning effects – as evidenced by a general speed-up of RTs with increasing practice (seen in pure form on distractor-absent trials) – in the present task, the most apt comparison to examine for this pattern is that between adjacent blocks, which minimizes the impact of general learning effects.

similar, though not reliable (7-ms increase with frequent-region distractors, t(46) = -0.89, p = .381; 9-ms decrease with rare-region distractors, t(46) = 0.72, p = .477) – which may simply be owing to the comparatively small distractor location probability cueing effect in this condition, making the differences hard to resolve statistically. This pattern is theoretically interesting because, at least with same-dimension-distractors, it suggests a trade-off in spatial inhibition between the frequent and rare distractors regions: more inhibition applied to the frequent region is associated with less inhibition for the rare region – consistent with the idea that there is a limited pool of inhibitory resources that can be distributed, unevenly or evenly, across the search array. Further work is necessary to corroborate this pattern and establish whether it holds not only for same-dimension (inhibition at the level of the overall-saliency map), but also for different-dimension distractors (dimension-based inhibition).

To sum up: The differential carry-over effects between the distractor types (same-dimension: orientation; different-dimension: color) supports our hypothesis that region-selective suppression of same-dimension distractors is based on different mechanisms than the suppression of different-dimension distractors. In particular, with same-dimension distractors, participants learn to (strongly) suppress any signal at the level of the overall-saliency map (in the frequent distractor area) and this suppressive set also applies to signals originating from a different dimension (after the switch from same-dimension to different-dimension distractors in Experiment 3). By contrast, with different-dimension distractors, the learning is dimension-specific: suppressing any feature contrast signals (exclusively) from the distractor-defining dimension.

In conclusion, we take our findings to show that when the probability cueing is learnt through spatial suppression mechanisms on the master saliency map, it is not only more persistent over time but also more resistant to un-/re-learning. This is in contrast to the more shallow learning of different-dimension distractors, which is not implemented on the overall-saliency map, but on the feature contrast maps for specific dimensions.

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Author contributions

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment, conducted the study and analyzed the data. Marian Sauter and Hermann Müller wrote and revised the manuscript.

Location probability cueing of luminance distractors

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Abstract

It is well-established that, in visual pop-out search, observers can exploit uneven distributions of item locations in order to facilitate search performance: at locations where they appear more often, targets are detected faster (f.e. Geng & Behrmann, 2002; 2005) and task-irrelevant distractors can be better suppressed (Goschy et al, 2014, Sauter et al, 2016; accepted). There are three plausible mechanisms of how the suppression of frequent distractors might work (Gaspelin & Luck, 2017). *First-order feature suppression models* assume that objects are suppressed on the basis of simple feature values (e.g., everything 'red' gets suppressed). *Second-order feature suppression models* assume that objects are suppressed on the basis of local discontinuities within feature dimensions, rather than feature values (effectively this means that distractor-defining dimensions are suppressed, e.g., everything that is colored differently than the search target gets suppressed). *Global-salience suppression models* assume that objects are not directly suppressed based on their features or feature dimensions, but rather their overall salience is reduced. Evidence in favor of first-order feature suppression models is usually limited to the color domain (c.f. Gaspelin & Luck, 2017) and a generalization of the results might not be possible, as in the orientation dimension in certain circumstances, there is no distractor learning (Liesefeld et al., 2017) and when there is learning, there are consistent target-location effects indicative of global-salience suppression (Sauter & Müller, 2017). The purpose of the present study was the generalization from the orientation dimension to the luminance dimension. Participants had to search for a luminance-defined singleton target in displays that contained luminance-defined distractors (same-dimension) or orientation-defined distractors (different-dimension). Similar to Sauter and colleagues (accepted), we found massive target-location effects for same-dimension (luminance) distractors, but not for different-dimension (orientation) distractors. The results are therefore only consistent with second-order feature suppression models, such as the dimension-weighting account.

Keywords: probability cueing, location suppression, luminance, second-order feature suppression, dimension-weighting account

Introduction

It is well-established that, in visual pop-out search, observers can exploit uneven distributions of target locations in order to facilitate search performance: targets are detected faster at locations where they appear more frequently (Anderson & Druker, 2010; Fecteau, Korjoukov, & Roelfsema, 2009; Geng & Behrmann, 2002; 2005) – providing evidence for a *probability cueing effect* (Geng & Behrmann, 2002). Likewise, task-irrelevant distractors can be better suppressed at locations where they appear more often. In a typical probability-cueing study (Goschy et al, 2014, Sauter et al, 2016; accepted), the authors presented a slightly tilted (i.e., orientation-defined) gray target bar among vertical gray non-targets arranged around several concentric circles. In half of the search arrays, one of the vertical non-targets was red, serving as a highly salient color-defined distractor. The distribution of the distractor location was manipulated in such a way that distractors appeared with 90% probability in one half of the display (frequent region) and with 10% in the other (rare region). Goschy et al. (2014) found distractor interference to be significantly reduced when the distractor was presented in the frequent compared to the rare region. This finding suggests that we cannot only exploit uneven spatial distributions when they are directly related to the response-relevant target but also in shielding search from distracting influences from task-irrelevant non-targets.

In the literature, there is a growing debate about the cognitive mechanism underlying attentional capture of task-irrelevant distractor singletons. There are three plausible mechanisms (Gaspelin & Luck, 2017). *First-order feature suppression models* assume that objects are suppressed on the basis of simple feature values (e.g., everything 'red' gets suppressed). *Second-order feature suppression models* assume that objects are suppressed on the basis of local discontinuities within feature dimensions, rather than feature values (effectively this means that distractor-defining dimensions are suppressed, e.g., everything that is colored differently than the search target gets suppressed). *Global-salience suppression models* assume that objects are not directly suppressed based on their features or feature dimensions, but rather their overall salience is reduced. In the study of Gaspelin and Luck (2017), observers had to look for color singletons in a probe-amplified attentional capture paradigm. By varying the relative frequency of color singleton distractors, Gaspelin and Luck (2017) found that distractor suppression was only possible when the color values were predictable. This provides evidence for first-order feature suppression models. However, Liesefeld et al. (2017) conducted a similar investigation in the orientation dimension. While singleton target bars were tilted 12° from the vertical, distractors were always tilted 45°. The distractors were therefore perfectly predictable. However, their results indicate that distractor suppression was not possible as no learning (i.e., interference reduction) took place over the course of the experiment. Additionally, a study by Sauter et al. (accepted) directly contrasted same-dimension distractors (90° tilted from the vertical) and different-dimension distractors (red items instead of gray) when observers had to search for an orientation target (12° titled). The results revealed a massive difference in distractor interference effects between same- and different-dimension distractors.

In the current literature, empirical evidence that is in favor of first-order feature suppression models is overwhelmingly shown with search targets defined by shape and distractors defined by color, or vice versa (e.g. Theeuwes, 2006; Hickey, McDonald, & Theeuwes, 2006; Kiss, Grubert, Petersen, & Eimer, 2012; Jannati, Gaspar, & McDonald, 2013; Burra & Kerzel, 2013; Wykowska & Schubö, 2011).

Based on this literature, it would appear plausible that an element of first-order feature suppression is involved in reducing interference from color distractors (see also Gaspelin, Leonard, & Luck, 2015). In accordance with this are studies in conducted to examine the dimension-weighting account (an inclusive second-order feature suppression model; e.g., Found & Müller, 1996) in which the color dimension proved to be special. It was the only one of the tested dimensions (color, motion, orientation) showing feature-specific inter-trial priming and trial-wise pre-cueing effects (e.g., Müller et al., 2003; Weidner, Pollmann, Müller, & von Cramon, 2002). This argues in favor of the notion that not all features and feature dimensions are equal (Nothdurft, 1993; Wolfe, Chun, & Friedman-Hill, 1995). Accordingly, generalizing from one feature dimension to others, especially if the claims drive from work on the color dimension, can be considered to be problematic.

On this background, the purpose of the present study was the generalization from the results of Sauter et al. (accepted) from the orientation dimension to the luminance dimension. Participants had to search for a luminance-defined singleton target in displays that could luminance-defined distractors (same-dimension) or orientation-defined distractors (different-dimension). Based on the prior results (which are in line with the dimension-weighting account), we expected distractor interference to be greater for same-dimension distractors than for different-dimension distractors; in addition, there would be a target-location effect, (likely) indicative of global salience-based suppression, for same-dimension distractors but not for different-dimension distractors. Restated, our hypotheses were the following:

1. Distractor interference (the difference in response times between distractor-present and distractor-absent trials) will be significantly larger when the distractors are defined by luminance than when they are defined by orientation.

2. Target-location effects (faster RTs for the rare distractor region than for the frequent distractor region) will be evident for luminance distractors only.

In order to test these hypotheses, we used essentially the same paradigm as Sauter and colleagues (accepted), but instead of an orientation-defined target, we introduced a luminance-defined target and the (additional singleton) distractors were either luminance-defined (same-dimension group) or orientation-defined (different-dimension group).

Methods

Participants

26[33] (12 female, 14 male) right-handed observers, with a median age of 26 (range: 18–40) years, participated in this experiment. They were recruited from the participant pool of the LMU Munich. All of them reported normal or corrected-to-normal vision (including normal color vision) and gave prior informed consent. They received 5€ (or 5 BP) or course credits in compensation.

Set-up

The experiment was conducted in a moderately lit test lab. The search displays were presented on a 1024px x 768px screen, at a refresh rate of 60Hz. Stimuli were generated with OpenSesame 3.1 (Mathôt, Schreij, & Theeuwes, 2012) using a Psychopy backend (Pierce, 2007). Observers issued their responses using a QWERTZ keyboard, by pressing the “x” or the “m” key with their left- or right-hand index finger, respectively. The screen background was black. The stimulus

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[33] We recruited 41 subjects but excluded 15 of them, because they did not show a probability cueing effect, thereby not interesting for our analyses, which require successful learning.

displays were similar to those used by Sauter et al. (accepted). They (illustrated in Figure 1) consisted of gray (RGB: 120, 120, 120; CIE [Yxy]: 46.6, 0.31, 0.32) vertical non-target bars (0.25° of visual angle wide, 1.35° high), with their geometric centers equidistantly arranged on three (imaginary) concentric circles with radii of 2°, 4°, and 6°, comprising 6, 12, and 18 bars, respectively. A further gray bar occupied the position in the center of the three circles. In every bar, there was a gap 0.25° in size, which was randomly located 0.25° from the top or the bottom of the bar. The singleton target (present on every trial) differed from the non-targets by its unique luminance: either it was slightly darker than the non-targets (RGB: 60, 60, 60; CIE [Yxy]: 11.0, 0.31, 0.32) or slightly brighter than the non-targets (RGB: 180, 180, 180; CIE [Yxy]: 103.2, 0.31, 0.32).

A singleton distractor was present in 50% of the trials. For one group of 14 participants, one of the (vertical) non-targets was extremely bright (RGB: 240, 240, 240; CIE [Yxy]: 192.0, 0.31, 0.32) instead of gray (i.e., a distractor defined in the same dimension as the target). This luminance contrast modulation ensured that the target was less salient than the distractor (Y = 11.0 or 103.2 vs. Y = 192.0). For the other group of 12 participants, one of the non-targets was tilted by 90° from the vertical (i.e. horizontal bar, a distractor defined in a different dimension than the luminance target). Targets and distractors were presented exclusively at positions on the intermediate circle, to ensure consistent feature contrast to the non-targets in their surround.

Design

The type of the singleton distractor (same vs. different dimension) was introduced as a between-subject factor. The distractor distribution (90% vs. 10%) was also manipulated between subjects. The distractor frequency differed between the top half of the display (ranging from the 10 o’clock to the 2 o’clock position on the intermediate circle) and the bottom half (ranging from the 4 o’clock to the 8 o’clock position) (see Figure 1). For half of the participants within each group, the top semi-circle was the frequent and the bottom semi-circle the rare distractor area, and vice versa for the other half (see below). Neither the distractor nor the target could appear at the 3 o'clock and 9 o'clock positions, as these positions could not be unambiguously assigned to the frequent or rare area.

The experiment consisted of a total 768 trials, presented in 8 blocks. When a distractor was present, it appeared in the frequent area with a probability of 90% and in the rare area with a probability of 10%. The target appeared equally often in both areas, with an equal probability for all 10 possible positions, but it never occurred at the same position as the distractor. The order of the trials within each block was completely randomized.

Procedure

The experimental procedure was identical to Sauter et al. (accepted). Observers were instructed, in writing and orally, that their task was to discern whether the target bar was interrupted (by a gap) at the top or the bottom. If it was interrupted at the bottom, they were told to press the "x" key; if it was interrupted at the top, they had to press the "m" key. They were informed that on some trials, there would be an extremely bright (same-dimension group) or, respectively, a horizontal (different-dimension group) distractor bar which they should simply ignore as it would be irrelevant to the task. They were not informed that the distractor was more likely to appear in one particular region.

Each trial started with a gray fixation cross in the middle of the screen for a random duration between 700ms and 1100ms. Then the search display appeared and stayed on until the observer gave a response indicating the gap position in the target bar. If the response was incorrect, the word "Error" appeared in the center of the screen for 500ms. Thereafter, the next trial started without a delay. After each block of trials, observers received RT and accuracy feedback and could resume the experiment at their discretion.

After completing the experiment, participants filled in a brief questionnaire, which was intended to gage whether they had any explicit knowledge of the singleton distractors' prevalence and spatial (frequency) distribution.

Analysis

For the analyses presented below, we opted for Cohen's *d* to assess effect sizes. Apart from classical frequentist measures, we further report 95% highest posterior density (HDP) intervals (essentially a Bayesian equivalent to confidence intervals), calculated using the "coda" package (Plummer et al., 2006) for R (R Core Team, 2014); and we report JZS BF_{10} Bayes factors (Rouder et al., 2009) with standard priors, calculated using the BayesFactor package (Morey & Rouder, 2015) for R, for hypothesis-guided t-tests.

Results

Results are being reported along the lines of Sauter et al. (accepted) to allow for direct comparison. First, the median correct RTs (3.1% errors excluded) were subjected to repeated-measures ANOVAs with the factors distractor condition and target location for both distractor types individually.

Our main prediction, deriving from the dimension-weighting account, was that the mechanisms underlying the distractor probability-cueing effect (evidenced by reduced interference by distractors in the frequent vs. the rare area) would give rise to impaired target processing only for targets defined within the same dimension as, but not targets defined in a different dimension to, the distractor and only for same-dimension targets located in the frequent, but not targets in the rare, distractor region.

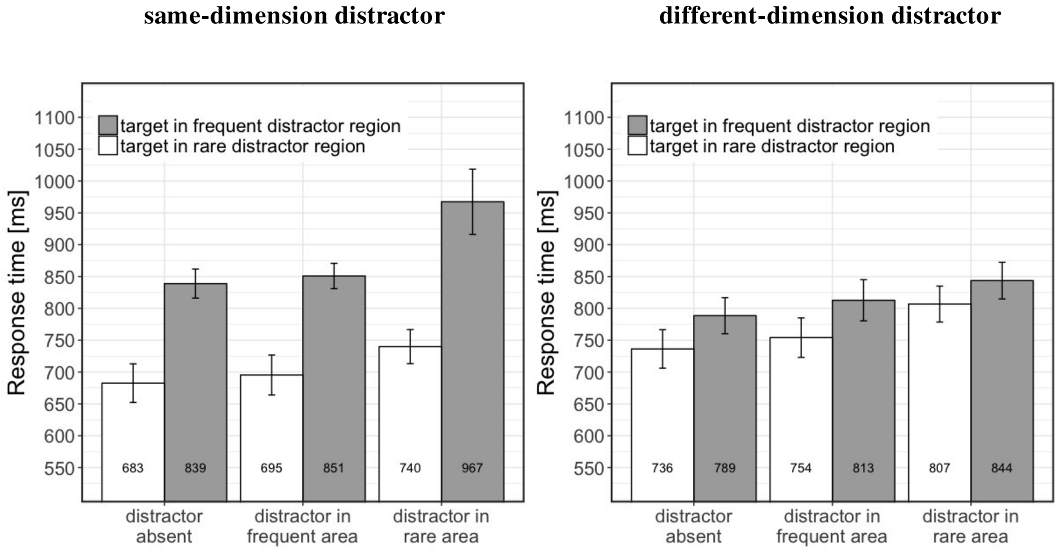

Figure 2. Mean RTs (calculated across participants' median RTs) for targets appearing in the frequent vs. rare distractor region as a function of the distractor condition (distractor absent, distractor in frequent region, distractor in rare region) for same-dimension distractors (horizontal, orientation-defined; panel A) and different-dimension distractors (red, color-defined distractor; panel B). Error bars depict the within-subject SEM (Morey, 2008).

Effects for same-dimension distractors

For same-dimension distractors, the ANOVA revealed both main effects to be significant (for visualization, see Figure 2): distractor location, F(2, 26) = 16.97, p < .001, η_p^2= 0.57, and target location, F(1, 13) = 11.73, p = .005, η_p^2 = 0.47; the interaction was also significant, F(2, 26) = 4.24, p = .025, η_p^2= 0.25.

To ascertain that distractors generally caused interference, we directly compared RTs on distractor-present trials with those on distractor-absent trials: RTs were overall slower when a distractor was present than when it was absent (769 ms vs. 750 ms; t(13) = 2.72, p = .009, dz = 0.73, 95% HPD [3 ms, 29 ms], BF_{10} = 7). To directly test for a probability-cueing effect, we contrasted the frequent versus rare distractor-present conditions: RTs were indeed faster, by 82 ms, when a distractor was presented in the frequent area compared to the rare area (760 ms vs. 842 ms), t(13) = -4.72, p < .001, dz = 1.26, 95% HPD [-114 ms, -38 ms], BF10 = 171). Finally, we examined the net distractor-interference effect with reference to distractor-absent trials for the frequent and rare areas separately. While distractors in the rare distractor caused significant interference (92 ms; t(13) = 5.63, p < .001, dz = 1.5, 95% HPD [49 ms, 121 ms], BF_{10} = 342), distractors in the frequent region did not (10 ms; t(13) = 1.5, p = .157, dz = 0.4, 95% HPD [-5 ms, 22.13 ms], BF_{10} = 0.6776). The latter, null-effect suggests that shielding of search from interference was near-perfect when distractors appeared in the likely region. .

Next, we tested the target-location effect separately for all three distractor conditions. For all three distractor conditions, RTs to targets in the frequent region were a substantially slower than to targets in the rare region (absent distractors: -156 ms; t(13) = -3.34, p = .005, dz = 0.89, 95% HPD [-226.3 ms, -32.14 ms], BF10 = 10; frequent distractors: -156 ms; t(13) = -3.4, p = .005, dz = 0.91, 95% HPD [-232 ms, -45 ms], BF10 = 11; rare distractors: -227 ms; t(13) = -3.28, p = .006, dz = 0.88, 95% HPD [-348 ms, -68 ms], BF10 = 8.726). Importantly, this effect was evident, and strong, even when distractors were absent, that is, when there could not be any distractor interference.[34] This pattern is (qualitatively) similar to that observed with same-dimension distractors in the orientation dimension. It indicates that the mechanism responsible for the suppression the frequent distractor area affects not only the processing of the (same-dimension) distractor, but also that of the target.

Effects for different-dimension distractors

For different-dimension distractors, the ANOVA also revealed a significant main effect for distractor condition F(2, 22) = 18.31, p < .001, η_p^2 = 0.62), but (in contrast

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[34] The significant interaction was due to the fact that the target-location effect was increased for the rare distractor area. Given that the RT estimates in this conditions are based on the smallest number of observation (and thus likely associated with the largest measurement error), we refrain from interpreting this effect.

to same-dimension distractors) not for target location (F(1, 11) = 0.91, p = .36, η_p^2= 0.08); the interaction was also not significant (F(2, 22) = 0.53, p = .595, η_p^2= 0.05).

Distractors again caused general interference (main effect of distractor condition): RTs were slower on distractor-present compared to distractor-absent trials (776 ms vs. 754 ms; t(11) = 3.55, p = .002, dz = 1.02, 95% HPD [6 ms, 33 ms], BF_{10} = 22); note that this interference effect was comparable in magnitude to that of same-dimension distractors. Furthermore, a comparison of the frequent versus the rare distractor-present condition revealed RTs to be indeed faster when a distractor was presented in the frequent area compared to the rare area (772 ms vs. 816 ms), t(11) = -4.79, p < .001, dz = 1.38, 95% HPD [-61.39 ms, -20.07 ms], BF10 = 130), though this probability-cueing effect, was much smaller compared to that with same-dimension distractors (44 ms vs. 82 ms). Finally, as expected, the net distractor interference effect with reference to distractor-absent trials was greater for distractors in the rare area (62 ms; t(11) = 5.19, p < .001, dz = 1.5, 95% HPD [29 ms, 82 ms], BF10 = 112) than for distractors in the frequent area (18 ms; t(11) = 3.14, p = .009, dz = 0.91, 95% HPD [4 ms, 30 ms], BF10 = 6).

Concerning the (non-significant) target-location effect, RTs were numerically somewhat slower to targets in the frequent versus targets in the rare distractor area. This effect was non-significant for all three distractor conditions (distractor absent: -52 ms; t(11) = -0.99, p = .345, dz = 0.29, 95% HPD [-141 ms, 63 ms], BF10 = 0.4322; distractor in frequent area: -59 ms; t(11) = -1.03, p = .323, dz = 0.3, 95% HPD [-148 ms, 57 ms], BF10 = 0.4489); distractor in rare area: -37 ms; t(11) = -0.75, p = .471, dz = 0.22, 95% HPD [-123 ms, 62 ms], BF10 = 0.3645).

Discussion

The present study revealed differences in the probability cueing effect between same- and different-dimension distractors when searching for a luminance target, but also similarities. Both distractor types show significant interference effects. Interestingly, these interference effects are of similar magnitude, which was not the case in the orientation dimension (Sauter et al., accepted). When searching for an orientation target, the (same-dimension) orientation distractor interfered massively compared to the interference caused by the (different-dimension) color distractor. One reason for this might lie in the saliency. In the present study, the same-dimension distractor was darker than the non-targets and thus less discriminable from the black background, possibly lowering its saliency. However, since saliency is hypothesized to reflect local feature contrast, rather than specific feature value, of an item (Wolfe, 2006), this is unlikely the only explanation, as local feature contrast incorporates target-nontarget contrast on top of target-background contrast. Independently of this, an issue with luminance distractors is that balancing four different luminance values (background, nontargets, target, and same-dimension distractor) can be a challenging task to optimize.

Unexpectedly, we found near-perfect learning in the frequent distractor region for same-dimension distractors: there was no significant difference to the distractor-absent condition anymore. This shows that it is in fact possible to nullify attentional capture by distractors purely by applying top-down search strategies – in the present case, applying sufficient suppression to the frequent distractor region (though not to the rare region). This is at variance with earlier, influential views that this is impossible (Theeuwes, 2004).

In a similar fashion to the study by Sauter and colleagues (accepted), we found massive target-location effects for same-dimension (luminance) distractors, but not for different-dimension (orientation) distractors. These differences cannot be explained by spatial versions of pure first-order feature suppression models or pure global-salience based models: the former would predict no target-location effects at all, whereas the latter would predict target-location effects for both distractor types. The results are therefore only consistent with second-order feature suppression models, such as the dimension-weighting account. In these, the suppression of feature dimensions (or feature discontinuities) leaves target processing unaffected (i.e., without giving rise to a target-location effect) if and only if the target and distractor are defined in different dimensions. If they are defined in the same dimension, in line with the dimension-weighting account, there would be two possible suppression mechanisms: dimension-based suppression or a fallback to global-salience based suppression. Both of these strategies can effectively suppress the distractor. However, because neither strategy can differentiate between target and distractor, they both give rise to a target-suppression effect in the frequent region, where the most suppression is applied.

In conclusion, while both distractor-type groups showed similar amounts of learning of the spatial distractor distribution (as evidenced by reduced interference from distractors that appeared in the frequent, as compared to the rare, distractor area), same-dimension distractors caused massive target-location effects, while different-dimension distractors did not. The results therefore are interpreted in favor of second-order feature suppression models, like the dimension-weighting account. Importantly, the results show that for participants who show location probability learning, effects are qualitatively comparable across dimensions. Therefore, observers might apply similar mechanisms to suppress same-dimension or different-dimension distractors irrespective of the actual target dimension, implying that the validity of second-order feature suppression models, like the dimension-weighting account, could potentially be shown across visual dimensions.

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Author contributions

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed and conducted the study. Marian Sauter analysed the data. Marian Sauter wrote the manuscript. Marian Sauter and Hermann Müller revised the manuscript.

General Conclusion

This thesis set out to investigate the mechanisms underlying the probability cueing effect of distractor locations, that is, the ability to selectively, or better, suppress distracting objects in a region where they appear most often, compared to a region where they appear only rarely. In the beginning, we identified three possible ways in which such a spatially selective distractor suppression might be implemented in the hierarchical organization of the visual system.

1. **Global spatial suppression**: Spatial shielding might operate at the level of the master saliency map. Reduced interference from distractors in a frequent region is attributable to a global bias, which inhibits the allocation of attention to this region. Put differently, saliency signals arising in this region are globally down-regulated, that is, or more strongly down-regulated compared to rare distractor regions.

2. **Feature-based spatial suppression**: Spatial shielding might operate at a level below the master saliency map, where local feature contrast signals are computed. Distractor suppression could operate on the feature maps, down-modulating the distractor-defining feature directly, with stronger down-modulation applied to the frequent as compared to the rare region.

3. **Dimension-based spatial suppression**: Spatial shielding might operate at a level below the master saliency map, which integrates feature-contrast signals across the various stimulus dimensions. Specifically, distractor suppression would be realized by down-modulating the strength of all feature-contrast signals in the dimension in which the distractor is singled out from the non-targets, with stronger down-modulation of signals in the frequent versus the rare distractor region. This is the possibility envisioned by the dimension-weighting account, and formed our working hypothesis.

We tested this hypothesis by comparing and contrasting the effects of same-dimension versus different-dimension distractors in several studies employing the (distractor location) probability cueing paradigm. In the first study entitled '*Region-based shielding of visual search from salient distractors: Target detection is impaired with same- but not different-dimension distractors*', we were the first to employ a distractor location probability cueing paradigm with both same-dimension and different-dimension distractors, to directly examine for differential distractor interference and target location effects. Participants had to look for a slightly tilted target bar among other vertical bars (orientation-defined target). In half of the trials, there was no distractor (distractor-absent trials). In the other half, one of the non-targets was red (different-dimension distractor, between-participant variable) or horizontal (same-dimension distractor, between-participant variable). The results revealed massive distractor interference effects in the same-dimension distractor condition, as compared to much smaller interference in the different-dimension distractor condition. In addition, a distractor location probability cueing effect (i.e., reduced interference by distractors in the frequent vs. the rare region) was acquired in both conditions, though this effect was much more marked for the same-dimension, as compared to the different-dimension, condition.

Crucially, also, for same-dimension distractors, targets were responded to slower when they appeared in the frequent distractor region, and this was the case even on distractor-absent trials. By contrast, no such target location effect was evident for different-dimension distractors. This qualitative difference between same- and different-dimension distractors was reliably established in the present study (with 184 participants), furthering our understanding of the functional architecture of search guidance: Given this pattern, it is most plausible to conclude that same-dimension distractors are largely suppressed by a global space-based mechanism (operating at the level of the master saliency map, where one region may be more inhibited than another region), while suppression of different-dimension distractors operates at a dimension-based level (i.e., feature-contrast signals from the distractor-defining dimension are down-weighted and so contribute less to master map activation, with stronger down-weighting of signals in the frequent vs. the rare distractor region).

Assuming that same-dimension distractors give rise to greater ‘surprise’ (as evidenced by 4 times higher interference) than different-dimension distractors, it is necessary to engage a greater degree of ‘controlled processing’ (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) to establish and optimize control routines to minimize distractor interference. We predicted this would ultimately lead to deeper learning and better long-term memory of where distractors are likely to appear with same-dimension as compared to different-dimension distractors.

Based on this conjecture, we examined whether the learning (of the distractor distribution) is persistent over time and still evident after a 24h waiting period – in a second study entitled ‘*Location probability cueing persists over time for same-dimension but not different-dimension distractors*’. The study followed a two-stage logic. First, it was designed to test the hypothesis that distractor location probability learning is ultimately better consolidated in long-term memory with same-dimension distractors as compared to different-dimension distractors. Participants learned the (uneven) distractor distribution in the ‘standard’ paradigm in the first session, and we then assessed whether there would still be a probability cueing effect in the second session after 24 hours, in which the distractor distribution was even, that is, distractors were equally likely to occur in the previously frequent and rare regions (i.e., there could not be any reinforcement of the uneven distribution, only unlearning of this distribution by the new, even distractor statistics). The results showed that the probability cueing effect reflects long-term learning of the likely distractor locations: the effect increased gradually with time on the task and was still evident in the second session (i.e., 24 hours plus after initial learning) – critically however: only with same-dimension distractors (significant cueing effect), but not with different-dimension distractors (non-significant effect). This means that for same-dimension distractors, the acquired suppression bias (acquired under a controlled mental set) is more deeply engrained and the corresponding control routines still tend to be retrieved even when the initially learned distractor distribution does no longer apply (in the test session), and unlearning takes several hundred trials to adapt to the even distribution.

Second, we went on to examine whether whatever strategy is acquired on day 1 to deal with same-dimension distractors would be independent of the learned object (i.e. the specific same-dimension distractor). The results demonstrated that a probability cueing effect established with same-dimension distractors in the learning session does carry over (after 24 plus hours) to the test session with different-dimension distractors. This carry-over across the two distractor types (same-dimension → different dimension) supports our working hypothesis that region-selective suppression of same-dimension distractors is based on a different mechanism than the suppression of different-dimension distractors. We take this carry-over effect to corroborate that with same-dimension distractors, the acquired distractor location probability cueing effect is implemented in terms of differential suppression applied to the (frequent vs. rare region on the) master saliency map; this implementation is not only more persistent over time (and so more resistant to un- or re-learning), but also transfers to distractors defined in another dimension – because the overall-saliency map is a supra-dimensional (i.e., dimension- and feature-blind) representation. This is in contrast to the shallower learning of (the distribution of) different-dimension distractors, which is not implemented on the overall-saliency map, but on the specific feature-contrast maps for the (different) distractor dimensions.

In the attentional-capture literature, evidence in favor of first-order feature suppression models is usually limited to the color domain (c.f. Gaspelin & Luck, 2017). However, a generalization of this conclusion to other stimulus domains might not be possible, as in the orientation dimension, under certain circumstances, there is only very limited shielding from distractors even after extensive practice (Liesefeld et al., 2017), and when shielding routines are acquired, there are consistent target-location effects indicative of global-salience suppression (Sauter et al., accepted). The purpose of the study entitled '*Location probability cueing of luminance distractors*' was to generalize this pattern from the orientation dimension to the luminance dimension. Among moderately bright nontargets, participants had to search for a slightly darker target. In half of the trials, one of the nontargets was a very bright distractor (same-dimension condition) or a horizontal distractor (different-dimension distractor). Similar to our investigations in the orientation dimension, we found massive target-location effects for same-dimension (luminance) distractors, but not for different-dimension (orientation) distractors. The results are therefore more, or only, consistent with second-order feature suppression models (rather than first-order suppression models), such as the dimension-weighting account.

In parallel to the previous investigations, we set out to elucidate the mechanisms involved in the probability cueing effect by means of event-related potential analysis in the study entitled '*The location probability cueing effect is revealed by ERP components*'. The N2pc is a negative-going deflection, at around 200 ms after the onset of the search display, which is elicited contralateral to the target item (predominantly) at posterior electrodes. It is interpreted as a common neurophysiological marker for the allocation of visuo-spatial, or 'focal', attention (Luck and Hillyard, 1994). The related P_D is a positive-going deflection elicited shortly after attention is allocated to a distractor (often seen instead of a distractor-N2pc) and interpreted as evidence of active distractor suppression (Hickey, Lollo, & McDonald, 2009). Our (ERP) study (which focused on same-dimension, orientation-defined distractors only) revealed, somewhat unexpectedly, that distractors in both the frequent and rare distractor regions elicited an N2pc component, though only as a statistical trend for rare distractors. The interpretation would be that attention was allocated to both frequent- and rare-area distractors, though more consistently to distractors in the frequent region. Additionally, a distractor-P_D was elicited for both frequent- and rare-area distractors, indicative of active top-down suppression recruited to mitigate distractor interference in both situations. The N2pc amplitude was also larger for frequent-area (vs. rare-area) distractors, which might indicate that a larger amount of attentional resources is required to attend to the distractor stimulus in the region that is suppressed at the global-salience level. This pattern of results generally argues in favor of a more efficient distractor handling process (at the global-salience level) that can be recruited for dealing with learned distractors.

In conclusion, the research conducted as part of this PhD project was a first look at the mechanisms of learned distractor shielding in visual search. The results demonstrated that suppression of same-dimension distractors differs from suppression of different-dimension distractors, with same-dimension distractors defined in both the orientation dimension and the luminance dimension (vs. different dimension-distractors defined in the color and, respectively, the orientation dimension). Same-dimension distractors gave rise to massive interference, a conclusive target-location effect, consistent N2pc-components in the frequent region, long-term persistence (over a 24-hour period), and carry-over to another distractor-defining dimension, indicative of a strong component of general, spatial suppression of the frequent versus the rare distractor region, which we propose operates at the level of the master saliency map. For different-dimension distractors, there was less interference overall, no target-location effect, and no long-term persistence. While the probability-cueing effect is also attributable to an element of differential spatial suppression between the frequent and rare distractor regions, it operates at a level prior to the search-guiding master saliency map, selectively down-modulating feature-contrast signals from the distractor dimension so that they register only weakly on the master saliency map.

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Curriculum Vitae

Education

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10/2008 – 09/2012 **B.Sc. in Cognitive Science**, University of Osnabruck

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Teaching Experience

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WT 2014 & 2015: Seminar „ScientificWork“, (“Wissenschaftliches Arbeiten”), for B.Sc. students, LMU Munich (14 sessions each)

WT 2014: Block seminar „Introduction to Neuroeconomics”, for B.Sc. and M.Sc. students, University of Osnabruck (6 sessions)

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Conferences

Sauter, M., Liesefeld, H. R., & Müller, H. (2017). Learning to shield visual search from salient distractors: Evidence from the N2pc component. Poster presentation at the Vision Sciences Society Annual Meeting 2017

Sauter M., Müller H., (May 2016) Learning to shield visual search from salient distractors, *Talk, 42. Tagung "Psychologie und Gehirn" Berlin, 26.–28. Mai 2016*

Sauter M., Müller H., (May 2016) Learning to shield visual search from salient distractors: qualitative differences in location probability cueing between same- and cross- dimensional distractors, *Poster presentation, Vision Sciences Society Annual Meeting, St. Pete Beach, FL, USA*

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List of publications

Sauter, M., Liesefeld, R., Zehetleitner, M., & Müller, H. (accepted). Region-Based Shielding of Visual Search from Salient Distractors: Target Detection is Impaired with Same- but not Different-Dimension Distractors. *Attention, Perception and Psychophysics* [*Manuscript accepted*]

Sauter, M., Liesefeld, H., & Müller, H. (2017). Learning to shield visual search from salient distractors: Evidence from the N2pc component. *Journal of Vision*, *17*(10), 1137-1137. [conference abstract]

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Soutschek, A., **Sauter, M.**, & Schubert, T. (2015). The Importance of the Lateral Prefrontal Cortex for Strategic Decision Making in the Prisoner's Dilemma. *Cognitive, Affective, & Behavioral Neuroscience*, 15(4), 854-860.

Affidavit

Hiermit versichere ich an Eides statt, dass ich die vorliegende Dissertation *Learning to shield visual search from salient distractors* selbstständig angefertigt habe, mich außer der angegebenen keiner weiteren Hilfsmittel bedient und alle Erkenntnisse, die aus dem Schrifttum ganz oder annähernd übernommen sind, als solche kenntlich gemacht und nach ihrer Herkunft unter Bezeichnung der Fundstelle einzeln nachgewiesen habe.

I hereby confirm that the dissertation *Learning to shield visual search from salient distractors* is the result of my own work and that I have only used sources or materials listed and specified in the dissertation.

München, 02.06.2018 Marian Sauter

München, den/Munich, date Unterschrift/Signature

Declaration of Author Contributions

Region-based shielding of visual search from salient distractors: Target detection is impaired with same- but not different-dimension distractors

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment. Marian Sauter collected the data (with help of Mallissa Watt and Paul Ricci) and analyzed the data. Marian Sauter and Hermann Müller wrote the manuscript. MS, HM, MZ and HL revised the manuscript. Marian Sauter is the only first author.

The location probability cueing effect is revealed by ERP components

Marian Sauter, Heinrich Liesefeld and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment, conducted the study and analyzed the behavioral data. Marian Sauter and Heinrich Liesefeld analyzed the EEG data. Marian Sauter and Heinrich Liesefeld wrote the manuscript. Marian Sauter is the only first author.

Location probability cueing persists over time for same-dimension but not different-dimension distractors

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed the experiment, conducted the study and analyzed the data. Marian Sauter and Hermann Müller wrote and revised the manuscript. Marian Sauter is the only first author.

Location probability cueing of luminance distractors

Marian Sauter and Hermann Müller conceived of the experiment. Marian Sauter programmed and conducted the study. Marian Sauter analysed the data. Marian Sauter wrote the manuscript. Marian Sauter and Hermann Müller revised the manuscript. Marian Sauter is the only first author.

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