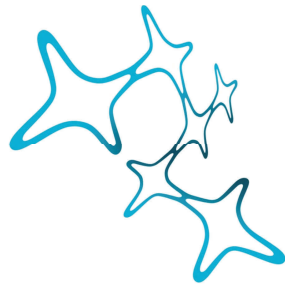

**A PROBABILISTIC THEORY OF SALIENCE:
ATTENTIONAL SELECTION AND CAPTURE**



Dissertation

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A PROBABILISTIC THEORY OF SALIENCE: ATTENTIONAL SELECTION AND CAPTURE

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Für meine Familie.

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Summary

Environment-driven attentional selection is assumed to be guided by the output of a salience map, which codes the conspicuity of each location in the visual field. Attentional selection sequence has been computationally modeled by salience and visual search models and has been empirically investigated with the distractor search paradigm. In this paradigm, a salient target and an additional salient distractor are presented among non-targets with the task to find the target and to ignore the distractor. The typical finding is that reaction times are increased when the salient distractor is present compared to when it is absent. It was concluded that attention is spatially captured by the more salient distractor before the target can be selected and that this additional selection leads to interference. However, this conclusion about the selection sequence is strongly debated and an alternative explanation is that attention is immediately directed to the less salient target, but this selection being slowed due to the distractor drawing processing resources. Although the attentional selection sequence, i.e. the source of reaction time interference, in the distractor search paradigm is still under debate, computational models as well as the empirically substantiated attentional capture account assume that the most salient location is invariably selected first.

The results of this thesis challenge this strong claim: by parametrically manipulating target and distractor salience in the distractor search paradigm, it was shown that the size of reaction time interference varies as a function of relative salience between target and distractor and that less salient distractors interfere as well. Empirical support that this interference is the result of spatial attentional capture rather than a slowed target selection was given by first saccades that were captured by the distractor and the influence of distance between target and distractor on reaction time interference. Furthermore, the shape of the distributions of reaction time interference matched the predictions of a capture account but was at variance with slowing theories. The empirical reaction time interference pattern was also replicated by computational simulations using a capture modeling architecture, which once more supports attentional capture as source of reaction time interference.

However, the results are also contradictory to the deterministic attentional capture account which claims that the most salient stimulus is always selected first. Instead, the probabilistic

theory of salience was developed to explain the results of this thesis. According to this theory, salience is a random variable with an expected mean value and an associated distribution. Analogously to a decision process, salience of each stimulus is accumulated over time until a selection threshold is reached and an attentional selection is triggered. Because the accumulation process is subject to noise, selection times of the stimuli follow a distribution and vary for different instances. As a consequence, attentional capture in the distractor search paradigm is probabilistic and distractors less salient than the target can capture attention when their selection time distributions overlap with the selection time distribution of the target. It is proposed that environment-driven attentional selection is probabilistically dependent on salience and that the most salient location is selected first only with a certain probability.

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1 Introduction

Everyday life is a sequence of little goals that belong to a superordinate goal. In order to achieve all these goals, focal attention is needed to concentrate on goal-relevant information and ignore all irrelevant signals that are constantly impinging on the sensory organs. Efficient attentional guidance to relevant objects is therefore a crucial function in human life. But how this guidance is accomplished in a specific situation is still an open question.

On the one hand, attentional allocation can be human-controlled, meaning it follows humans' intentions in a top-down manner; on the other hand, attentional deployment can be environment-driven, meaning it is automatically attracted by an object in a bottom-up fashion, which was not intended to be focused by the human (e.g. Egeth & Yantis, 1997). Most likely, both processes interact to determine the ultimate target of attentional selection. For the interaction of both attentional mechanisms (automatic vs. controlled), a two-stage architecture has become prominent (Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989; Wolfe, 1994): in the first stage, the pre-attentive stage, all stimuli in the visual field are processed automatically and in parallel with unrestricted processing resources. In the second stage, focal attention serially scans the field in a certain order with the processing capacity to control this order being limited. When a stimulus automatically attracts attention, the serially controlled focus of attention in the second stage is automatically oriented first to the stimulus that was denoted most conspicuous by the pre-attentive processing stage. In other words, the pre-attentive stage controls the focus of attention in this case.

In everyday life, this automatic capture of attention is known as distraction and is, at first glance, an undesirable condition. However, from an evolutionary perspective, it is indeed helpful: while concentrating on one goal, life-threatening stimuli, despite being irrelevant for the task at hand, can be detected in time and the human survives. However, in everyday life, unwanted attentional capture happens far more often than just through life-threatening stimuli. The conditions under which stimuli automatically attract attention have been debated

at length in research about attentional selection. The concept of salience, which is assumed to influence the output of the pre-attentive stage, plays a major role in this discussion.

The next sections of this introduction outline the concept of salience and its role in attentional selection, a frequently used paradigm to investigate automatic attentional selection and its main findings, as well as competing theories to explain these findings. At the end of the introduction, the aims of this thesis and the way they were achieved are specified.

1.1 Salience and selection processes

The concept of a map that codes conspicuity in the pre-attentive stage was theoretically discussed and supported by behavioral studies (Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe et al., 1989), but there have also been many attempts to model bottom-up salience algorithms (Bruce & Tsotsos, 2009; Gao & Vasconcelos, 2009; Itti & Koch, 2000; C. Koch & Ullman, 1985; Li, 2002) and simulate attentional selection in visual search behavior (Cave & Wolfe, 1990; Wolfe, 1994). Visual search is typically investigated by presenting participants with a stimulus display (or a natural image) and a task to find a pre-defined object. Such a stimulus display can be for instance a field of bars that are all vertically aligned, but one bar differs from the others in the orientation dimension in that it is tilted. The tilted bar in this context typically pops out from the background and can thus be efficiently found, that is the search time is the same, regardless of the number of bars surrounding it. How this parallel processing of all stimuli is achieved in the pre-attentive stage is subject to the salience models.

1.1.1 Salience models

Stimuli that attract attention automatically are different from all the other stimuli, meaning that they stand out from their background. In the visual domain, this distinctiveness is assumed to be described by a map that codes the physical contrast of all stimuli in the field.

This map is referred to as salience map. The stimulus attaining the highest activation on this salience map, i.e. the stimulus with the highest contrast, is automatically selected.

The basic idea of the salience map, as it was first described by C. Koch and Ullman (1985), is that each stimulus is compared to its neighboring stimuli and the more it differs from them, the higher is its activation signal on the map. These salience signals carry information about the spatial location of the stimulus so that spatial attention can be allocated to the strongest signal. To compute the activation signal of each stimulus location, in a first step, stimuli are pre-attentively decomposed into their low-level features. That is, as each stimulus is the synthesis of a certain color, intensity, orientation, size, and so forth, neighboring stimuli are compared on this level and contrast maps are computed by a center-surround algorithm for all feature-channels in parallel. In each of these maps, high contrasts of the respective feature are coded with a strong signal. In a second step, all feature map signals are integrated into the salience map that codes the location, which is overall most salient, regardless of the feature dimension that caused the strong signal. A winner-take-all mechanism then automatically guides the attentional focus across the scene in a salience decreasing order, starting with the most salient location. Figure 1 shows the salience map computation for a typical bottom-up salience model.

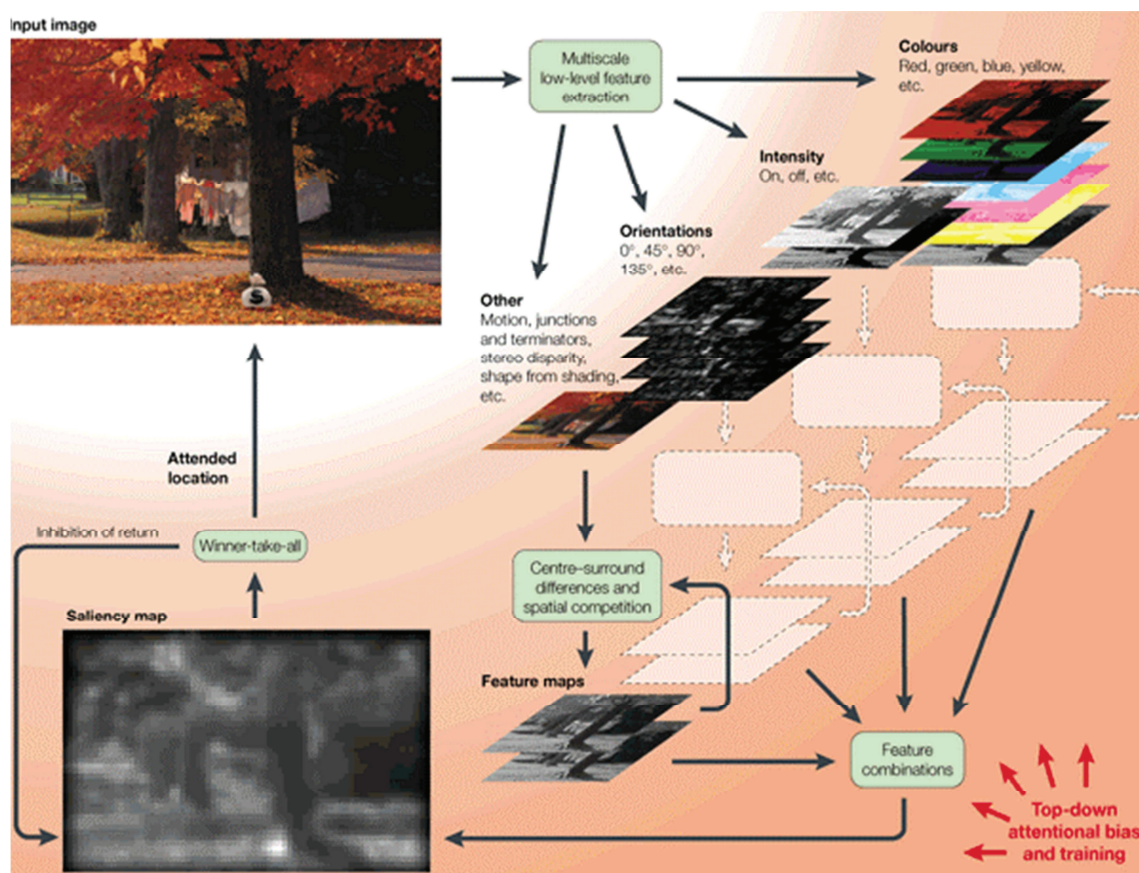


Figure 1. Typical model of bottom-up salience computation. An image is decomposed into its features of different dimensions. Contrast maps are created for low-level features, which are then integrated into an overall saliency map. Attention automatically selects the location with the strongest saliency signal. Reprinted by permission from Macmillan Publishers Ltd: Nature Reviews Neuroscience. Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews Neuroscience*, 2, 194–203, copyright 2001.

While this basic principle of salience computation is widely agreed on, the location of the salience map in the brain is still under debate. Most support is given to the lateral intraparietal area (Bisley & Goldberg, 2010; Gottlieb, Kusunoki, & Goldberg, 1998; Gottlieb, 2007) and the frontal eye fields (Moore & Armstrong, 2003; Thompson & Bichot, 2005) as locations for the salience map. Li (2002) suggested the primary visual cortex as site, but her salience model differs from the others in that no integration of different feature maps (a saliency map) is required to extract salience.

1.1.2 Visual search models

Visual search models intend to explain search behavior based on bottom-up and top-down influence. The most prominent model, Guided Search (Cave & Wolfe, 1990; Wolfe et al., 1989; Wolfe, 1994), is based on the two-stage architecture of attention with a pre-attentive, parallel processing stage and a subsequent attentive, serial processing stage. The activation map, which guides attentional selection, is similar to the salience map in that the activations of the feature maps are integrated into an overall, feature independent, activation map and activation strength is determined by the difference between one stimulus and its surrounding stimuli. This parallel processing stage, which suggests locations for focal attention, is then followed by a serial deployment of attention to the possible target locations in order of decreasing activation.

What distinguishes Guided Search from salience models is the assumption of noise in the selection process. Because early vision processes are influenced by noise, there is also variability in the activation map signal. That is, the mean activation signal for a specific location on the map is derived through the mechanisms described in the previous paragraph and specified by salience models, but the selection in a given situation is the mean value plus a noise component. Thus, Guided Search regards the search for a target as a signal detection problem where the activation of all non-targets is noise and the target activation is the signal plus noise. The stronger the signal is compared to the noise, i.e. the more salient a respective target is the more efficient is search.

Treating attentional selection in visual search as a signal to noise problem accounts for noise in the selection process, but disregards a time course at the same time. However, this is essential as even Wolfe (1994) states that “it is more reasonable (. . .) to assume that activations are continuously updated” (Wolfe, 1994, p. 229). A time course has never been considered, neither in salience nor in visual search models. Decision models on the contrary use a different model approach and consider a time component. The next section illustrates the model approach of decision models and how time is incorporated in these architectures.

1.1.3 Visual search as decision process

Visual search can be regarded as a chain of decisions (Wolfe & Van Wert, 2010; Wolfe, 1994; Zehetleitner, Rangelov, & Müller, 2012): first, a stimulus needs to be selected (decision between all stimuli), second, the selected stimulus is to be identified as target or distractor, third, the appropriate response has to be chosen, and last, a decision about the correct motor command has to be made. Although in principal decision making is a separate field of research, it is worth looking at the modeling architecture, because it considers temporal dynamics, which are missing in all models of salience-based selection.

In decision research, a common modeling approach is sequential sampling models (Ratcliff & Smith, 2004) such as the Ratcliff diffusion model (Ratcliff, 1978) or the (leaky) accumulator model (Usher & McClelland, 2001). The basic assumption of these models is that sensory evidence is accumulated continuously over time until a threshold is reached and a decision is triggered. The accumulation progresses with a particular mean gradient per time unit, the so-called drift rate, and a certain variance of this rate, which is the noise in the decision process. In other words, the models account for time and random fluctuations in information processing. The drift rate represents the speed at which a decision is made on average and it depends on the strength of the sensory signal: evidence of strong sensory signals is accumulated with a high drift rate; hence it reaches the threshold in a shorter period of time than evidence of weak signals, which is accumulated with a low drift rate. Figure 2 illustrates the basic principle of an accumulator model.

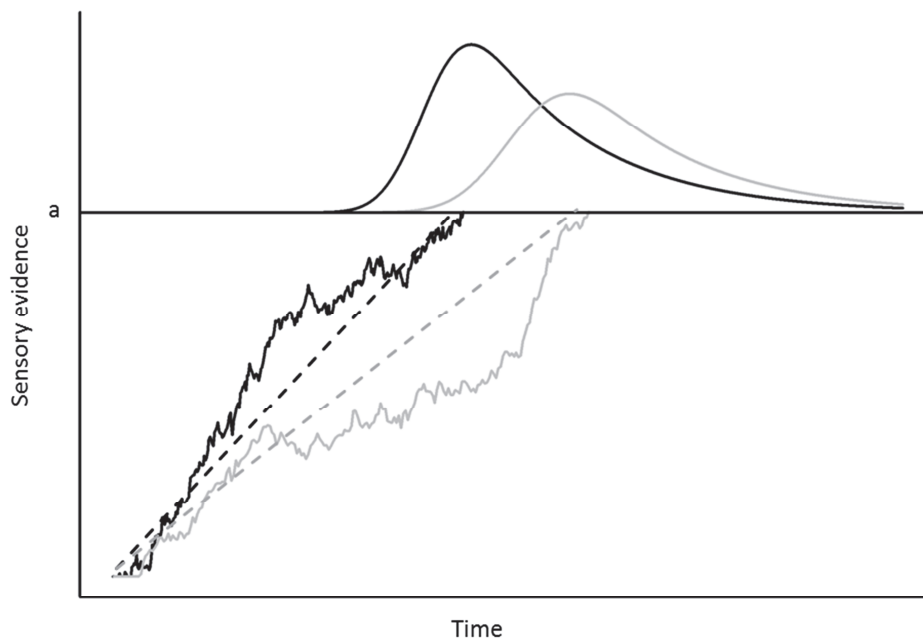


Figure 2. Decision process in an accumulator model. Depicted is the accumulation of sensory evidence as a function of time. Evidence of a stronger signal accumulates with a high drift rate (black dashed line) and evidence of a weak signal accumulates with a low drift rate (gray dashed line). For both drift rate examples, one sample accumulation path is presented, which is influenced by noise (jagged lines). A decision is triggered as soon as one accumulator hits the threshold a . The decision process is subject to noise, which is also indicated by the distribution of decisions times (above the threshold). Note that most often reaction instead of decision times are modeled. In this case, a non-decision time parameter (not displayed here) is added to the decision time to account for time not related to the decision process, such as perceptual or motor processes.

1.2 The distractor search paradigm

An established paradigm to investigate salience-based attentional selection is the distractor search paradigm (Theeuwes, 1991, 1992). In this paradigm, one salient target-stimulus is presented among a set of homogeneous non-target stimuli and on some trials, an additional salient, but task-irrelevant stimulus is presented. While the target has to be attentionally selected, the salient distractor has to be ignored. In the original task (Theeuwes, 1992), the homogeneous non-target set was comprised of green diamonds and one green circle that were arranged in a circle around the center of the computer screen. The green circle was the to-be-detected target. In half of the trials, one green diamond was replaced by a red diamond – this was the salient distractor. Participants had to search for the green circle and indicate (via

button press) the orientation of the line segment, which was enclosed by the circle. The fact that the response criterion (the line segment) was different from the target-defining feature (circle form) ensured that focal attention was directed to the target stimulus and the selection process was disentangled from the response decision.

The main finding of this study was that reaction time was prolonged when the red distractor was present compared to when it was absent (Theeuwes, 1992). That is, the red distractor interfered with the search for the target circle. This reaction time interference disappeared when the target was color-defined and the distractor was presented in the odd-one-out shape. It was assumed that the reaction time interference was the result of attentional capture by the distractor before the target selection. That is, the focus of attention had to detour via the distractor location before engaging with the target location. Because reaction time interference occurred only when the distractor was in the color and the target in the shape dimension (and not the other way around), the conclusion was that salience is the critical factor for the first attentional selection. The distractor captures attention automatically when it is more salient than the target, but if the target is more salient than the distractor, it can be selected first and the less salient distractor does not interfere. In principle, this is in line with the predictions of bottom-up salience models, but as pointed out below, predictions of these models are more precise.

1.3 The source of reaction time interference in the distractor search paradigm

The main finding of the distractor search task is that reaction time interference occurs when a visually salient distractor is present. In the original study, it was concluded that spatial attentional capture by the distractor caused this reaction time interference (Theeuwes, 1992). However, this conclusion is controversial and has been extensively discussed in the literature. There are other conceivable sources of reaction time interference. For instance, instead of being captured by the distractor, attention could directly be oriented towards the target location, but this selection is slowed owing to simultaneous distractor processing (Becker, 2007; Folk & Remington, 1998; Wykowska & Schubö, 2010). With respect to the

assumption that focal attention scans the visual field serially, both possible sources of reaction time interference differ when it comes to the number of necessary selections until the target stimulus is found: whereas the attentional capture account claims two selections, namely a first distractor and a subsequent target selection, the slowing theory assumes only one selection, which is the immediate target selection. Figure 3 schematically illustrates three conceivable sequences of target selection.

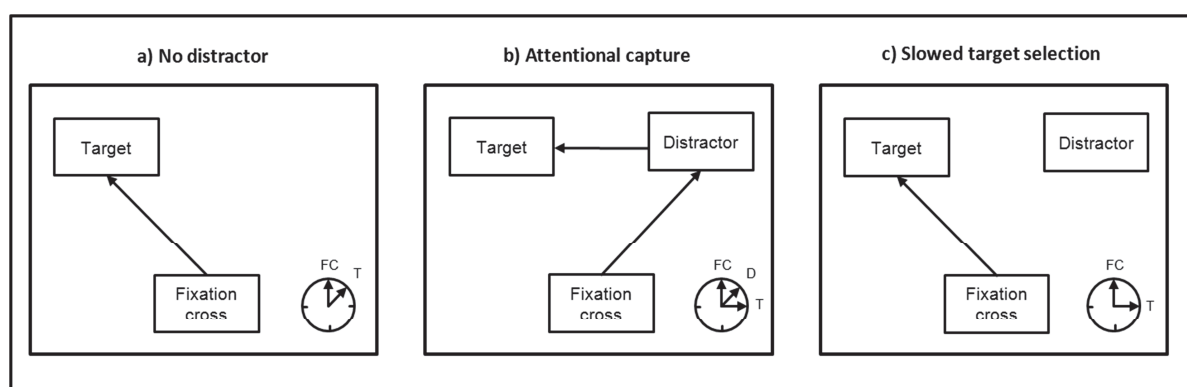


Figure 3. Conceivable selection sequences in the distractor search paradigm. a) When no distractor is present, but only the target, attention is directed straight from the fixation cross to the target. This takes a certain amount of time. b) If a distractor is present, the attentional capture account assumes a first selection of the distractor location and a subsequent target selection. These two selections cost more time than only one target selection. c) If a distractor is present, the slowing theory expects the target location to be selected first, but because the distractor is drawing processing resources, this selection is slowed compared to when there is only the target present. Spatial allocation of attention is indicated by boxes and arrows; time is displayed through the clock symbols (both not drawn to scale). FC = Fixation cross, T = Target, D = Distractor.

While the location of the first selection (distractor vs. target) has been subject to a vigorous debate (e.g. Bacon & Egeth, 1994; Becker, 2007; Leber & Egeth, 2006; Müller, Geyer, Zehetleitner, & Krummenacher, 2009; Theeuwes, 1991, 1992, 2010; Wykowska & Schubö, 2010; Zehetleitner, Goschy, & Müller, 2012; Zehetleitner, Müller, & Proulx, 2009; Van Zoest, Donk, & Theeuwes, 2004; Van Zoest & Donk, 2005; Zwaan et al., 2010), the target selection after attentional capture, i.e. the second selection, has been neglected as possible contributor to reaction time interference in the distractor search paradigm. In addition to the competing accounts of attentional capture and slowing there are different views about the mechanisms of how capture or slowing could proceed: attentional capture could be deterministically dependent on salience (Theeuwes, 2010) or could fluctuate and

therefore be probabilistically dependent on salience, as noise in the neural system distorts the signal emanating from the physical stimuli (C. Koch & Ullman, 1985; Wolfe et al., 1989; Wolfe, 1994). In terms of the slowing accounts, non-spatial filtering (Becker, 2007; Folk & Remington, 1998; Wykowska & Schubö, 2010) or spatial competition between both stimuli (Beck & Kastner, 2005, 2009; Desimone & Duncan, 1995; Desimone, 1998) is assumed to delay the target selection, i.e. the first selection. All four possible mechanisms of reaction time interference in the distractor search paradigm as well as the target selection after attentional capture are introduced in detail in the following sections.

1.3.1 Attentional capture

The distractor search paradigm was used to empirically investigate the order of attentional selection. Because reaction time interference occurred only when the distractor was more salient, but not when it was less salient than the target (Theeuwes, 1992), it was concluded “that the initial shift of attention [is directed] to the most salient singleton” (Theeuwes, 2010, p. 80) and “that the bottom-up salience signal of the stimuli in the visual field determines the selection order” (Theeuwes, 2010, p. 81). This deterministic view about salience-based selection has become very influential; yet it was established after testing only two conditions of distractor salience, namely a distractor more and one less salient than the target. However, salience-based visual search theories assume noise to influence salience computation on some processing stage(s) (Cave & Wolfe, 1990; Wolfe et al., 1989; Wolfe, 1994). These theories would therefore predict a probabilistic dependency between attentional capture and selection order in the distractor search paradigm. A probabilistic dependency implies that the most salient stimulus captures attention not with certainty, but only with a certain probability. This also includes distractors less salient than the target to interfere with search, although with a lower probability. Moreover, the second (target) selection as additional influence on reaction time interference has been completely ignored in the deterministic attentional capture account. Hence the questions whether attentional selection order is deterministically or probabilistically dependent on salience and whether the second selection after attentional capture also contributes to reaction time interference are still open and empirical evidence is pending.

1.3.2 Slowed target selection

One of the main competitive explanations of attentional capture as source of reaction time interference is the theory of non-spatial filtering (Folk & Remington, 1998). It is assumed that the target is attentionally selected first, but the presence of the distractor prolongates this selection. The theory is based on the findings of Kahneman, Treisman, and Burkell (1983) that responses to a target object are slower when it is presented among task-irrelevant objects, compared to when it is presented alone. This reaction time difference was attributed to a filtering process by which the irrelevant objects are filtered out in order to identify the target. This filtering process is assumed to be a non-spatial competition for selection between the stimuli (Folk & Remington, 1998; Wykowska & Schubö, 2010). Although the theory of non-spatial filtering is based on findings from a different paradigm in which target and distractor are not simultaneously presented, it also makes predictions for the distractor search paradigm: because the filtering process is assumed to be non-spatial, any effect of distance between target and distractor on reaction time interference argues against a non-spatial process and disproves non-spatial filtering as source of reaction time interference in the distractor search paradigm. The influence of target-distractor distance has therefore been used to test non-spatial filtering as source of reaction time interference: Becker (2007) compared conditions where the distractor was next to the target with those where at least one non-target was in between. Although she found an effect of distance on reaction time interference, she did not completely rule out non-spatial filtering because the error pattern was indicative of a speed-accuracy trade-off in the data, which restricts the reliability of the effect. Wykowska and Schubö (2010) chose a different approach to test for non-spatial filtering by using the event-related EEG component N2pc as indicator of attentional capture. This component is assumed to be a marker of the spatial allocation of attention (Eimer, 1996). Wykowska and Schubö (2010) found that attention was always directed to the target location first and was not captured by the distractor. However, the onset latency of the component was longer when the distractor was presented in the opposite hemifield compared to when it was presented in the same hemifield as the target. That is, although attention was not spatially captured by the distractor, it nevertheless produced some delay in the allocation of attention to the target. The authors conclude that non-spatial filtering costs cause reaction time interference in the distractor search paradigm.

An alternative theory to explain slowed target selection is the biased competition model of selective attention (Desimone & Duncan, 1995). This theory is more elaborate than non-spatial filtering and its scope goes far beyond the distractor search paradigm. Biased competition postulates that simultaneously presented stimuli compete for selection, i.e. neural representation, this competition being biased by bottom-up mechanisms, such as salience (Beck & Kastner, 2005), or top-down control processes. Because of the underlying neural architecture, competition strength is assumed to be dependent on spatial relations between the competing stimuli: the neural representations of simultaneously presented stimuli interact in a mutually suppressive way (Desimone, 1998), which means that stimuli represented in close cortical areas are more competitive than stimuli represented in distant regions. Because in the primary visual cortex stimuli representations are topographically organized, close stimuli fall into the same receptive field, meaning they are represented by the same cluster of neurons, and therefore competition between those stimuli is stronger than for distant stimuli, which do not share the same processing sources (Beck & Kastner, 2009). In terms of slowed target selection in the distractor search paradigm, biased competition would predict distance between target and distractor to influence the competition among both, even if the target is selected before the distractor. In other words, distance should also influence the size of reaction time interference when the target is selected first. Of course it is also conceivable that the distractor wins the competition and is selected before the target. In this case, spatial competition would result in attentional capture by the distractor.

In summary, reaction time interference can result from competition processes that delay the first (target) selection without the distractor having spatially captured attention. If attention is not spatially captured by the distractor in the distractor search paradigm, it is yet unsolved whether the delay of the first target selection is the result of non-spatial or spatial competition processes.

1.3.3 Target selection after attentional capture

Once attention is captured by the distractor and the human realizes that the selected stimulus is not the target, attention needs to be redirected to the target. That is, a second selection has to be carried out. How this second (target) selection proceeds and whether it

also contributes to reaction time interference in the distractor search paradigm, is largely unexplored. This is all the more surprising because the deterministic attentional capture account assumes two selections (Theeuwes, 2010), but does not specify the exact source of reaction time interference. That is, it leaves open the question whether it is the first (distractor) selection, the second (target) selection, or both selections that contribute to reaction time interference.

1.4 Aim of the thesis

This thesis approached two main goals. First, answering the research question about the source of reaction time interference in the distractor search paradigm. Although extensively investigated, this has not been conclusively identified yet. Second, establishing a probabilistic theory of salience by introducing a more differentiated specification of the concept, including noise and temporal dynamics as model inherent components. This theory is based on the empirical findings regarding the source of reaction time interference. It explains these findings and makes predictions about attentional selection and capture.

To clarify the source of reaction time interference, the first (distractor vs. target) and the second (target) selection were investigated. To test whether the order of attentional selection is deterministically or probabilistically dependent on relative salience between target and distractor, the distractor search paradigm was advanced by introducing a parametric salience manipulation of target and distractor. To underpin the conclusion of (probabilistic) attentional capture as source of reaction time interference as against the hypothesis of a slowed first target selection, computational as well as empirical investigations were carried out: the results of the distractor search paradigm were computationally simulated with a binary capture model architecture: the model output was the proportion of attentional capture events instead of reaction time interference. Further, the influence of distance between target and distractor on reaction time interference was used to empirically rule out non-spatial filtering and the analysis of the reaction time interference distribution was taken to test for attentional capture versus spatial slowing, i.e. biased competition. In addition, one eye movement study was conducted to demonstrate oculomotor capture in the same paradigm,

which is closely related to attentional capture (Deubel & Schneider, 1996). To examine the role of the second (target) selection in reaction time interference, distribution analysis was used once more in a reaction time and an eye movement study. Figure 4 gives an overview about the possible sources of reaction time interference in the distractor search paradigm which were tested in the studies of this thesis.

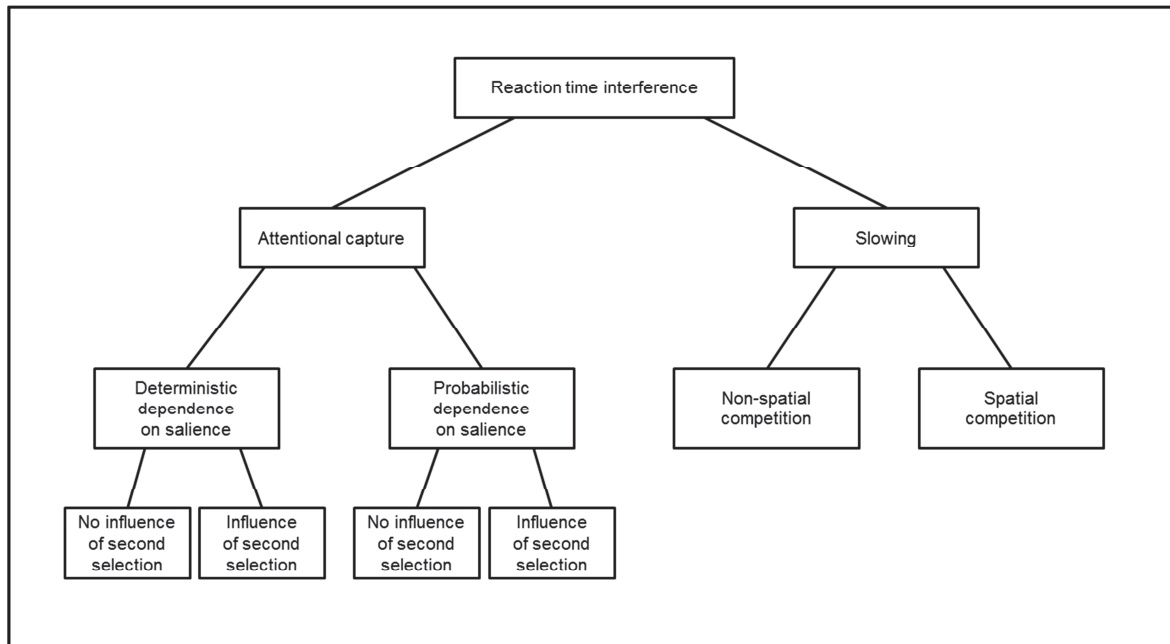


Figure 4. Possible sources of reaction time interference in the distractor search paradigm. Reaction time interference could be the result of attentional capture by the distractor or the consequence of a slowed target selection. In the former case, the occurrence of attentional capture could be deterministically or probabilistically dependent on stimulus salience and the second (target) selection could influence reaction time interference or not. In the latter case, slowing could emerge from non-spatial or spatial competition processes between target and distractor.

The probabilistic theory of salience includes noise and temporal dynamics as model inherent components. This theoretical concept treats salience-based selection as decision process with sensory evidence accumulating over time until a selection threshold is reached. Hence, it combines methods of decision research with principles of salience-based selection. For the computational implementation, the accumulator model (Usher & McClelland, 2001) was used in combination with empirically obtained salience measures.

2 Cumulative Thesis

This thesis consists of two articles, peer-reviewed and published in the journals *PLoS ONE* and *Acta Psychologica* and one article, which is to be submitted to a peer-reviewed journal. On the following pages, the abstracts of both articles and the manuscript are presented, along with the contributions of the author of this thesis. The full text of the articles and the manuscript are enclosed in the list of publications.

2.1 Saliency-based selection: Attentional capture by distractors less salient than the target

Zehetleitner, M.*, Koch, A. I.*, Goschy, H., & Müller, H. J. (2013). Saliency-based selection: Attentional capture by distractors less salient than the target. *PLoS ONE*, *8*(1), e52595.

Current accounts of attentional capture predict the most salient stimulus to be invariably selected first. However, existing saliency and visual search models assume noise in the map computation or selection process. Consequently, they predict the first selection to be stochastically dependent on saliency, implying that attention could even be captured first by the second most salient (instead of the most salient) stimulus in the field. Yet, capture by less salient distractors has not been reported and saliency-based selection accounts claim that the distractor has to be more salient in order to capture attention. We tested this prediction using an empirical and modeling approach of the distractor search paradigm. For the empirical part, we manipulated saliency of target and distractor parametrically and measured reaction time interference when a distractor was present compared to absent. Reaction time interference was strongly correlated with distractor saliency relative to the target. Moreover, even distractors less salient than the target captured attention, as measured by reaction time interference and oculomotor capture. In the modeling part, we simulated first selection in the distractor search paradigm using behavioral measures of saliency and considering the time course of selection including noise. We were able to replicate the result pattern we obtained in the empirical part. We conclude that each saliency value follows a specific selection time distribution and attentional capture occurs when the selection time distributions of target and distractor overlap. Hence, selection is stochastic in nature and attentional capture occurs with a certain probability depending on relative saliency.

The author of this thesis contributed to this article by conceiving and designing the reaction time and eye movement experiments, conducting the reaction time experiment and analyzing its data. Further, she contributed in developing the probabilistic theory of saliency

as well as its theoretical consequences for attentional capture. She also wrote the manuscript (except for the section *Computational Model*) and designed the figures and tables.

* Shared first authorship: these authors contributed equally to this work.

2.2 Distractors less salient than targets capture attention rather than producing non-spatial filtering costs

Koch, A. I., Müller, H. J., & Zehetleitner, M. (2013). Distractors less salient than targets capture attention instead of producing non-spatial filtering costs. *Acta Psychologica*, *144*, 61-72.

Distractors that are less salient than the target evoke reaction time interference in the distractor search paradigm. Here, we investigated whether this interference indeed results from spatial attentional capture or merely from non-spatial filtering costs. Target and distractor salience was manipulated parametrically and the modulation of reaction time interference by the distance between both stimuli was taken as an indicator of attentional capture. For distractors that were less salient than the target, we found distance to be predictive of reaction time interference. Moreover, this relationship was modulated by the difference in relative salience of target and distractor: the less salient the distractor was compared to the target, the weaker was the influence of distance. These results are in accordance with the sequential sampling model of salience-based selection by Zehetleitner et al. (Zehetleitner, M., Koch, A.I., Goschy, H., Müller, H.J., 2013. Salience-based selection: Interference by distractors less salient than the target. *PLoS ONE* 8: e52595.). This model assumes the salience map to be computed by noisy accumulation of sensory evidence. As a result, the salience map output fluctuates around its true value and less salient locations can be denoted as most salient. A distractor less salient than the target can therefore capture attention with a certain probability. We conclude that reaction time interference by less salient distractors in the distractor search paradigm is a result of attentional capture in a proportion of trials, rather than a result of non-spatial filtering costs.

The author of this thesis contributed to this article by conceiving, designing, and conducting the experiments and analyzing the data. Further, she wrote the manuscript and designed figures and tables.

2.3 Distribution analysis of reaction time interference: Speeded target selection after attentional capture

Koch, A. I., Müller, H. J., Goschy, H., & Zehetleitner, M. (2013). Distribution analysis of reaction time interference: Speeded target selection after attentional capture. Unpublished manuscript.

Interference in the distractor search paradigm, when a distractor is present compared to absent, is a frequently reported phenomenon. However, the source of this interference is unclear and debated. While some authors claim the additional time is the result from spatial attentional capture, others think that attentional deployment to the target is slowed due to filtering processes. By contrast, the second target selection after attentional capture by the distractor has hardly been investigated. To discriminate between spatial capture and slowed target selection and to investigate the second target selection, we qualitatively analyzed the distribution of reaction time and saccadic interference. Predictions about the distribution were generated by an accumulator race model and were qualitatively tested by two reaction time and one eye movement experiment. The results favor attentional capture as source for interference. Moreover, once attention was captured, the second target selection was faster than when no distractor was present. This result is explained by an immediate selection of the second most salient item. In conclusion, attentional capture by a distractor can slow target selection in some cases and speed it in other.

The author of this thesis contributed to this article by conceiving, designing, and conducting the reaction time experiments and analyzing the data of the reaction time and eye movement experiments. Further, she wrote the manuscript and designed the figures.

3 Discussion

Automatic attentional selection is assumed to be guided by the signals of a salience map, which codes the conspicuity of each location in the visual field. To investigate salience-based selection, the distractor search paradigm has frequently been used. It was found that response times to a target stimulus are prolonged when a salient distractor was presented together with the target, compared to when the target was presented alone or when the distractor was less salient than the target (Theeuwes, 1992). The source of this reaction time interference was however debated: on the one hand it was assumed that attention was spatially captured by the distractor before it could be directed to the target (Theeuwes, 1992, 2010). On the other hand it was claimed that the target is spatially selected first, but this selection is slowed because the distractor competes for processing resources (Becker, 2007; Folk & Remington, 1998; Wykowska & Schubö, 2010). For each of these explanations, further assumptions of how the interference producing mechanism could proceed are conceivable: attentional capture could be deterministically dependent on stimulus salience, meaning that a more salient distractor always captures attention, or it could be probabilistically dependent, in which case salience determines the probability with which a distractor captures attention. For competition processes that slow the target selection, non-spatial filtering processes or spatial competition, biased by salience, are two possible alternatives. In addition, for the attentional capture option, the second (target) selection could or could not have an influence on reaction time interference.

The aim of this thesis was to investigate the source mechanism of reaction time interference in the distractor search paradigm and, based on the findings, to establish a probabilistic theory of salience. To decide between deterministic and probabilistic capture, target and distractor salience was parametrically manipulated in the distractor search paradigm and results were computationally simulated with a probabilistic capture model architecture (Zehetleitner, Koch, Goschy, & Müller, 2013). The influence of target-distractor distance on reaction time interference ruled out non-spatial filtering mechanisms as source (A. I. Koch, Müller, & Zehetleitner, 2013), and the analysis of the distributions of reaction time interference revealed probabilistic attentional capture instead of spatial competition to

cause reaction time interference (A. I. Koch, Goschy, Müller, & Zehetleitner, 2013). The contribution of the second (target) selection to reaction time interference was revealed by examining the distributional instead of mean interference (A. I. Koch, Goschy et al., 2013). Figure 5 presents the framework of all studies that were carried out for this thesis and the identified source of reaction time interference in the distractor search paradigm.

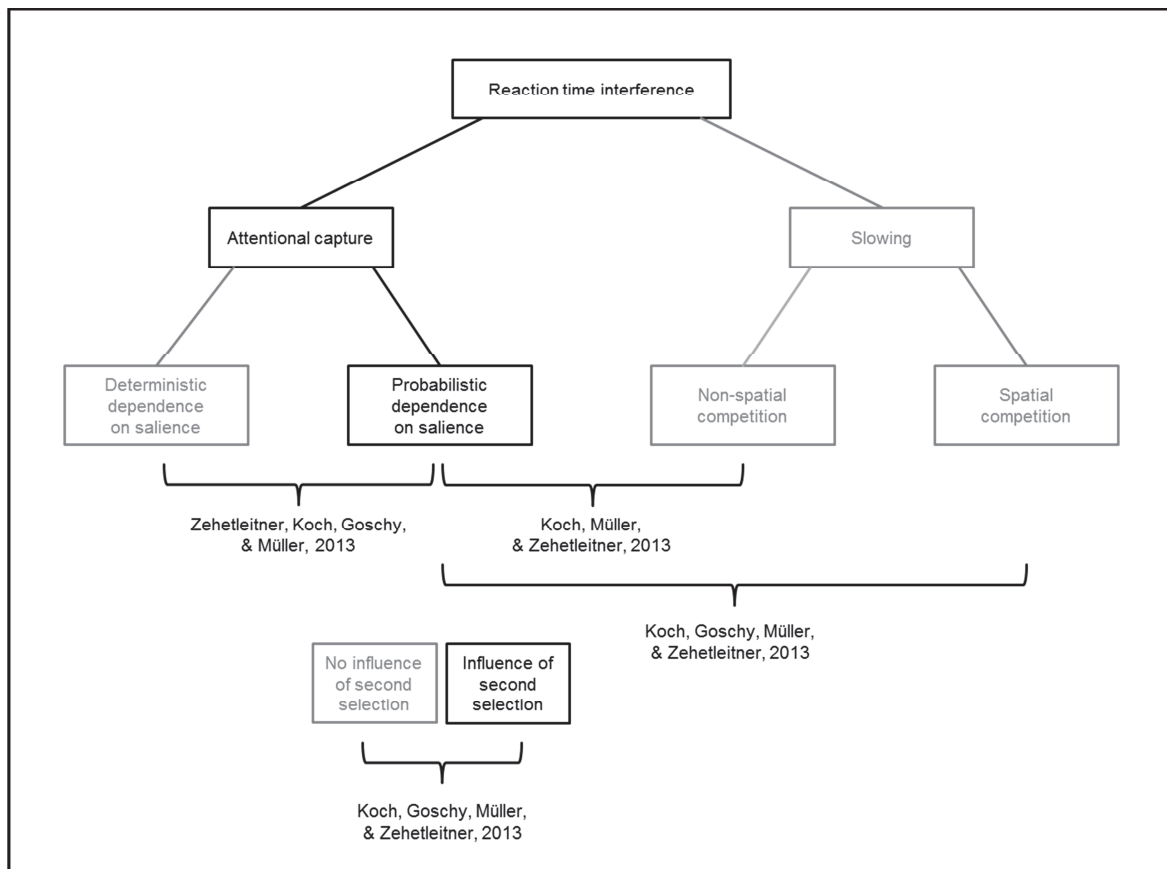


Figure 5. Study framework and identified source of reaction time interference. Three studies provided evidence for the probabilistic occurrence of attentional capture as source of reaction time interference in the distractor search paradigm. In addition, it was found that the second (target) selection also modulated reaction time interference.

3.1 Falsified theories of reaction time interference in the distractor search paradigm

The parametrical manipulation of target and distractor salience in the distractor search paradigm revealed a gradual increase of reaction time interference with increasing distractor relative to target salience (Zehetleitner et al., 2013). As a consequence thereof, distractors less salient than the target produced reaction time interference as well. Support that this interference (even by less salient distractors) was the result of attentional capture came from the computational simulation with a probabilistic capture architecture, which replicated the interference pattern of the behavioral experiment, and from an eye-tracking experiment, which showed that less salient distractors capture the gaze in some occasions (Zehetleitner et al., 2013). These results unambiguously refute the deterministic account of attentional capture, which claims that distractors more salient than the target always capture attention, whereas less salient distractors never capture attention (Theeuwes, 1992, 2010).

Non-spatial filtering explanations for the positive correlation between reaction time interference were excluded because target-distractor distance influenced reaction time interference (A. I. Koch, Müller et al., 2013). It was found that the closer together target and distractor were presented, the higher was reaction time interference. This effect is explained by a ring of suppression that is built around an attended location (Mounts & Gavett, 2004; Mounts, 2000). Once attention is captured by the distractor, the ring of suppression lies around the distractor location and a target that is closely situated to this location is more difficult to detect than a distant target. In other words, the distance effect serves as evidence of attentional capture by the distractor. In addition to the general occurrence of the distance effect, the effect was also observed for the subset of less salient distractors and was modulated by relative salience between target and distractor. These results refute the explanation of non-spatial filtering, but are in accordance with the findings of Zehetleitner et al. (2013), that reaction time interference is caused by probabilistic attentional capture: the more salient the distractor was compared to the target, the stronger was the distance effect pronounced, i.e. the more often the distractor captured the attentional focus.

Biased competition postulates competition for selection to be stronger for close objects and weaker for distant stimuli, that is it assumes competition to be spatially modulated (Desimone & Duncan, 1995). Hence according to this theory, the presence of a distance effect is not automatically attributed to attentional capture, but could also arise from spatial competition where the target is selected first. To distinguish between probabilistic attentional capture and spatial competition, the distribution of reaction time interference was analyzed, because both theories make different predictions about the distribution, although they expect the same mean interference (A. I. Koch, Goschy et al., 2013). The form of the reaction time interference distribution followed the predictions of a probabilistic capture account rather than of a non-capture, slowing theory.

Deterministic attentional capture, non-spatial filtering, and spatial slowing mechanisms as suggested by biased competition were falsified as source of reaction time interference in the distractor search paradigm. Instead, attentional capture probabilistically dependent on salience is proposed (A. I. Koch, Goschy et al., 2013; A. I. Koch, Müller et al., 2013; Zehetleitner et al., 2013). The theory to explain probabilistic capture and the role of the second (target) selection in reaction time interference is presented in the next section.

3.2 Probabilistic theory of salience

The development of the probabilistic theory of salience was motivated by the finding that reaction time interference in the distractor search paradigm varied as a function of relative salience between target and distractor and also less salient distractors interfered (Zehetleitner et al., 2013). The core assumption of the theory is the distinction between *stimulus* and *selection salience*. This distinction is possible because noise and temporal dynamics are considered in the salience computation process. Salience is assumed to be an entity that is subject to noise, meaning that the salience value that a stimulus attains on a certain instance is drawn from a distribution with an expected mean value of salience. The expected mean value of salience corresponds to the stimulus salience as computed by center-surround algorithms (e.g. Bruce & Tsotsos, 2009; Gao & Vasconcelos, 2009; Itti & Koch, 2000; C. Koch & Ullman, 1985), i.e. the distinctiveness of each stimulus from its surrounding stimuli.

Selection salience on the other hand is the actual value a stimulus with a given surround attains in a certain instance of time. In other words, while stimulus salience is constant, selection salience is a random variable across instances, due to the influence of noise.

The model architecture of this probabilistic salience concept is based on the accumulator race model (Usher & McClelland, 2001). It describes the translation of stimulus into selection salience by assuming that the salience map develops over time. Each stimulus is represented by an accumulator unit that accumulates stimulus salience over time, until a selection threshold is reached. The drift rate of each accumulator corresponds to the respective stimulus salience. Selection salience of a stimulus is the accumulated stimulus salience at the time its accumulator hits the threshold. By reaching the threshold, an attentional selection of this stimulus is automatically triggered. Because the accumulation process is noisy, selection salience deviates from the expected mean of the selection time distribution, i.e. it deviates from stimulus salience. The fact that salience is accumulated over time for each location implies that the salience map as a whole also evolves over time and is subject to noise. The pattern on the map differs depending on the time the first accumulator hits the selection threshold: the map computation stops at the moment the first accumulator reaches the threshold and the salience values of all other locations are determined by the level their accumulators have attained at that moment.

The probabilistic theory of salience explains the results presented in all articles of this thesis (A. I. Koch et al., 2013, in press; Zehetleitner et al., 2013): (i) size of reaction time interference depends on the distractor salience relative to the target's salience, (ii) distractors less salient than the targets capture attention, (iii) the effect of target distractor-distance on reaction time interference is modulated by relative salience, and (iv) reaction time interference increases over the first percentiles and decreases again in the last percentiles.

3.2.1 Probabilistic attentional capture

The size of reaction time interference depends on relative salience between target and distractor (Zehetleitner et al., 2013). The studies conducted for this thesis suggest attentional capture to be the source of reaction time interference (A. I. Koch, Goschy et al., 2013; A. I.

Koch, Müller et al., 2013; Zehetleitner et al., 2013). Because attentional capture is a discrete event (either it occurs or it does not occur on a given search trial), a varying size of reaction time interference can be explained by different proportions of capture and non-capture events: high mean reaction time interference is the result of a large proportion of capture trials plus a small proportion of non-capture trials and low mean reaction time interference is the consequence of a small proportion of capture trials plus a large proportion of non-capture trials. In other words, the proportion of attentional capture in the distractor search paradigm is dependent on relative salience between target and distractor. The mechanism behind this relationship can be explained by the probabilistic theory of salience.

In the distractor search paradigm, target and distractor are the only salient stimuli. Because they are pop-out stimuli, all other non-targets can be neglected in the selection process and the race for selection takes place between the target and the distractor, each represented by one accumulator unit. Relative salience between target and distractor is incorporated in the model as the difference in drift rates between both stimuli. Attentional capture occurs when the distractor accumulator hits the selection threshold before the target accumulator. The likelihood with which each stimulus reaches the threshold before the other stimulus is determined by the relative stimulus salience between both: the more salient the distractor is compared to the target, i.e. the faster its drift rate is, the more likely it is selected first and the less salient it is, i.e. the slower its drift rate is, the more likely the target wins the race. That is, the size of the proportion of capture trials is dependent on relative stimulus salience between target and distractor and capture can also occur for less salient distractors, as long as target and distractor selection times overlap. To illustrate this rationale, we imagine a target and a distractor which are equally salient. In this case, their drift rates are exactly the same and their selection time distributions fully overlap. Hence the likelihood of attentional capture by the distractor is 50% and the likelihood of the target hitting the threshold first is also 50%. This can be observed by a mean reaction time interference of intermediate size. The less salient the distractor is compared to the target, the slower is its drift rate compared to the target and thus selection time distributions of both stimuli drift apart. As a consequence, their overlap becomes smaller – and so does the probability for attentional capture and the size of observed reaction time interference.

To summarize, according to the probabilistic theory of salience, attentional capture is possible as long as the drift rate of the distractor is faster than the drift rate of the target or selection time distributions of target and distractor overlap. The probability for capture depends on the size of this overlap (for illustration of probabilistic attentional capture see Zehetleitner et al., 2013, Fig. 5).

3.2.2 Target selection after attentional capture

Attentional capture probabilistically dependent on relative salience between target and distractor concerns only the first selection. However, a second (target) selection has to be carried out in order to complete the task. While the first distractor selection could be the sole cause of reaction time interference and the subsequent target selection could proceed just as in trials without a distractor being present, it is also possible that the second target selection contributes to reaction time interference. That is, target selection could be different when a distractor is present compared to when it is absent.

Results of the analysis of reaction time interference distributions revealed that interference increased over the first percentiles and decreased again in later percentiles. In some cases, interference became even negative in the last percentile, which indicates that the presence of the distractor expedited search for the target instead of slowing it. While it is plausible that for slow response times the proportion of capture trials is higher and hence interference is higher, it seems counterintuitive that for very slow response times, interference decreases again or even becomes negative. The probabilistic theory of salience explains this surprising shape of the distribution of reaction time interference and unveils the influence of the second selection when searching for a target in the presence of a distractor.

Attentional capture occurs when the accumulator of the distractor hits the selection threshold before the target accumulator. If the second (target) selection would be the same as in trials where there is no distractor present, the attentional system would simply wait until the target accumulator hits the threshold to select the target. However, since the second most salient stimulus can only be the target in the distractor search paradigm, it is more efficient to select the second most stimulus – the target – immediately, instead of waiting until it reaches

the threshold. This earlier target selection can be achieved by lowering the selection threshold after the distractor has been identified as wrong stimulus. The selection threshold is lowered to the level of accumulated target evidence at the time of distractor selection plus the disengagement time. This process allows for the target to be selected earlier when a distractor is present compared to when it is absent, that is it antagonizes reaction time interference. The gain of time due to lowering the selection threshold is the greater the slower the target selection time is compared to the distractor selection time: if the target selection time is only a little slower than the distractor selection time, the target accumulator will reach the threshold while attention is still in the process of disengagement from the distractor and hence lowering the threshold has no effect on target selection time. However, if the target selection is many times slower than the distractor selection, the target accumulator has not reached the threshold at the time attention has disengaged from the distractor and lowering the threshold expedites target selection. In cases of extreme selection time difference, earlier target selection not only reduces or neutralizes reaction time interference produced by the distractor, but even changes it to the contrary, namely speeded reaction times when a distractor is present compared to absent.

In summary, the influence of distractor and subsequent target selection on the size and algebraic sign of reaction time interference are antagonistic: while the presence of the distractor increases reaction time interference, the subsequent target selection can reduce interference again (for illustration see A. I. Koch, Goschy et al., 2013, Fig. 1).

3.3 Methodological contributions

The invention of the probabilistic theory of salience and the investigation of the source mechanism of reaction time interference in the distractor search paradigm was achieved by the introduction of several new methods or the application of established methods to a new research area. First, salience was parametrically manipulated in the distractor search paradigm and empirically measured. Second, the modeling architecture of decision models was applied to the research field of salience. Third, the distribution of reaction time interference was analyzed instead of mean interference.

In the original study (Theeuwes, 1992) and subsequent investigations (e.g. Donk & Van Zoest, 2008; de Fockert, Rees, Frith, & Lavie, 2004; Hickey, McDonald, & Theeuwes, 2006), salience in the distractor search paradigm was manipulated in a binary fashion, that is the distractor was either more or less salient than the target. This led to the oversimplified conclusion that attentional capture is deterministically dependent on relative salience between target and distractor and that it is always the most salient stimulus in the visual field that captures attention first. A parametrical manipulation however, as shown here, reveals the possibility to account for the more complex and stochastic relationship between salience and attentional selection. At the same time it covers a broader range of the salience spectrum and hence allows detecting qualitative differences of the relationship between salience and attentional selection. Thus it could be discovered that the correlation was sigmoidal instead of linear, that is at the lower end of the relative salience spectrum, reaction time interference approached zero and at the upper end, it approached an asymptote where interference did not increase further with greater distractor salience. Also the empirical measurement of salience entails advantages: first, it accounts for the fact that salience is a psychological construct and is not linearly related to physical contrast (Nothdurft, 1993), and second, it makes stimuli of different dimensions directly comparable on the same scale.

The salience pattern computed by existing salience models is the same for several selection trials (Bruce & Tsotsos, 2009; Gao & Vasconcelos, 2009; Itti & Koch, 2000). That is, noise is not considered for the selection process and hence it is always the same item that is selected first. Whereas noise is implemented in Guided Search (Wolfe, 1994), this model still neglects the temporal dynamics in the development of the salience map. To account for both, noise and temporal dynamics, the probabilistic salience model (Zehetleitner et al., 2013) is grounded on a modeling architecture well-known in decision (Gold & Shadlen, 2007), but hitherto not applied in salience research: in sequential sampling models, sensory evidence is accumulated until a decision threshold is reached. By regarding salience-based selection as decision among n (number of stimuli in the field) alternatives and differentiating between stimulus and selection salience, an analogy to decision research can be drawn and the same architecture can be applied to salience computation: stimulus salience is accumulated until a selection threshold is reached. This modeling architecture allows for noise and temporal dynamics inherent in the salience computation process and thus

complements and advances existing theories of salience-based selection. In addition, it provides the foundation for different predictions about the distribution of reaction time interference, i.e. it makes the distinction between capture and non-capture accounts possible (see below), and reveals alternative mechanisms of the second selection in the distractor search paradigm (A. I. Koch, Goschy et al., 2013).

Reaction time interference in the distractor search paradigm has hitherto only been investigated by analyses of the mean (e.g. Becker, 2007; de Fockert et al., 2004; Leber & Egeth, 2006; Müller et al., 2009; Theeuwes, 1992). However, there is indication that means can be misleading for understanding effects in reaction time research and predictions of different theories can be indistinguishable for means, but are divergent for distributions (Balota & Yap, 2011). Empirical evidence for varying influence of salience on performance is given by accuracy data of eye movement studies using the distractor search paradigm, which suggest that the influence of salience changes with saccadic latency (Donk & Van Zoest, 2008; Godijn & Theeuwes, 2002; Van Zoest et al., 2004; Van Zoest & Donk, 2005, 2008). However, distribution of reaction time interference has not been analyzed yet. Using distribution analysis for reaction time interference the first time, we could distinguish between attentional capture accounts and non-capture theories (A. I. Koch, Goschy et al., 2013). Moreover, the contribution of the second selection after attentional capture to reaction time interference could be identified. The mechanism of this selection has been neglected in all studies investigating reaction time interference in the distractor search paradigm. The analysis of the distribution of reaction time interference gives new insight into the selection sequence and the nature of the single processes in the distractor search paradigm. It is thus obvious that this method opens up new possibilities for investigating salience-based selection.

3.4 Future directions

Although this thesis makes a comprehensive contribution to the understanding of reaction time interference in the distractor search paradigm by considering both the probabilistic occurrence of attentional capture for the first selection and the subsequent target selection,

there are still open questions about the source of reaction time interference in the distractor search paradigm and its neural correlates and there is potential to increase predictability of attentional selection based on the probabilistic theory of salience.

The likelihood of attentional capture, as determined by the probabilistic theory of salience, is solely based on the bottom-up, environment-driven factor of salience. However, there is evidence that top-down control operates early in the attentional system (Müller & Krummenacher, 2006) and visual search theories such as Guided Search (Wolfe, 1994) assume selection to be influenced by top-down activation. Even authors of pure bottom-up salience models acknowledge the impact of top-down control (Itti & Koch, 2001; see also Fig. 1). Neurophysiological approaches suggest a ‘priority’ instead of a ‘salience’ map, which combines bottom-up salience and task relevance in order to determine the location for the attentional focus (Fecteau & Munoz, 2006). Also the brain area, which is suggested as site of the salience map combines bottom-up and top-down signals (Bisley & Goldberg, 2010) in a way that resembles the dynamics of a decision process (Gold & Shadlen, 2007). Therefore, a next step in developing the probabilistic theory of salience would be to include observer-guided control. This could be implemented in the model for example by a faster drift rate of the target accumulator, which would imply that the target’s stimulus salience is higher and consequently its selection probability is increased.

Besides the model adaptation for the first selection, the second selection needs to be investigated more extensively as well, since this was the very first study examining this selection (A. I. Koch, Goschy et al., 2013). The qualitative inspection of the distributions of reaction time interference suggests that it is only the first selection that varies as a function of relative salience, because increase of reaction time interference over the first percentiles is varyingly strong for the various salience differences, but the amount of decrease in later percentiles seems to be the same for all salience differences. However, this is only a qualitative inspection and it is possible that especially the disengagement process from the distractor is also salience-dependent to a certain degree.

In general, it would also be interesting to investigate the selection sequence in the distractor search paradigm with respect to neural correlates of the reaction time interference

pattern. EEG would be an appropriate method with a high temporal resolution. The EEG event-related potential N2pc, which is regarded as a marker of spatial orientation of attention (Eimer, 1996), could provide confirming evidence about proportionate attentional capture: the N2pc indicates attentional deployment by negative deflection of cortical activity contralateral to the attended location. In case of attentional capture by the distractor, this event-related potential should occur for the distractor and subsequently for the target location. If the distractor did not capture attention, only an N2pc for the target should be visible. Moreover, if the size of the proportion of capture is dependent on distractor relative to target salience, the amplitude of the distractor N2pc should vary as a function of this salience difference, because - analogously to reaction time interference - a high mean amplitude should result from many capture trials and a low amplitude from few capture trials. If slowed target processing also contributes to reaction time interference, as predicted by non-capture theories, there should also be a latency effect of the N2pc observable that is its onset should vary with relative salience.

Another method neural correlates of reaction time interference could be investigated with is functional magnetic resonance imaging (fMRI). This method has the advantage of high spatial resolution and would help to identify areas in the brain that process salience-based attentional selection. Manipulating global and local salience in Navon figures, Mevorach, Humphreys and Shalev (2006) found reaction time interference from the low salient distractor to increase when transcranial magnetic stimulation (TMS) was applied to the right posterior parietal cortex (PPC). On the other hand, interference from the higher salient distractor increased when TMS was applied to the left PPC. The authors concluded that the right PPC is involved when orienting towards a salient target stimulus and the left PPC being responsible for avoidance of salient stimuli. In an fMRI study using the same paradigm (Mevorach, Shalev, Allen, & Humphreys, 2008), the left intraparietal sulcus was significantly more activated when attending to a less salient target in the presence of a higher salient distractor compared to a higher salient target accompanied by a less salient distractor. Moreover, the blood-oxygen-level-dependent (BOLD) response difference between distractors more salient and less salient than the target correlated positively with reaction time interference. The advantage of the Navon Paradigm is that effects of salience on the PPC activation can be discerned from spatial influences, however salience of target and

distractor is correlated and a manipulation always affects both stimuli. This problem is circumvented in the distractor search paradigm, where target and distractor are spatially separated and can therefore be manipulated independently with respect to their salience. Based on the findings of Mevorach et al. (2006) and Mevorach et al. (2008), activation of the right PPC should increase with decreasing distractor salience in the distractor search paradigm, if the right PPC is responsible for orienting towards salient items. On the other hand, if the left PPC is responsible for avoiding salience, its activation should increase with increasing distractor salience. Therefore, activation in right and left PPC should be negatively correlated if they had dissociative and complementary roles in attentional salience-based selection. Additionally, as Mevorach et al. (2008) showed, the BOLD-response should correlate with reaction time interference.

Last but not least the theory of probabilistic salience needs to be tested on other paradigms than the distractor search paradigm to generalize its field of application. The ultimate objective should be to predict the selection sequence in natural images.

3.5 Conclusion

The salience map, which is the basis for environment-driven attentional selection, depicts the conspicuousness of each location in the visual field. It evolves over time and is influenced by noise during its development. As a result, the focus of environment-driven attention is not always directed towards the most conspicuous object, but can prefer a less salient object if noise distorts the true salience pattern on the map. To account for these fluctuations, salience needs to be regarded as a random variable with a certain mean and an associated distribution. This is captured by the distinction between stimulus and selection salience: whereas stimulus salience is the mean (or expected) salience value of an object, i.e. the distinctiveness of this object to its surround, selection salience corresponds to the outcome of the salience map computation process, which is subject to noise and can therefore deviate from the mean. Accordingly, environment-driven attentional selection is probabilistically dependent on salience.

An empirical consequence of the probabilistic dependency between attentional selection and salience is that the proportion of attentional capture in the distractor search paradigm is dependent on relative salience between the target and the distractor, as indexed by reaction time interference distributions and first saccades. This implies that distractors less salient than the target are also able to capture attention in a proportion of trials, as long as their selection time distributions overlap with the selection time distribution of the target. According to the probabilistic theory of salience and the results presented in the studies of this thesis, reaction time interference in the distractor search paradigm is the consequence of proportionate attentional capture and an expedited subsequent target selection, rather than a slowed (first) target selection as proposed by non-capture theories.

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List of Publications

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Salience-Based Selection: Attentional Capture by Distractors Less Salient Than the Target

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Abstract

Current accounts of attentional capture predict the most salient stimulus to be invariably selected first. However, existing salience and visual search models assume noise in the map computation or selection process. Consequently, they predict the first selection to be stochastically dependent on salience, implying that attention could even be captured first by the second most salient (instead of the most salient) stimulus in the field. Yet, capture by less salient distractors has not been reported and salience-based selection accounts claim that the distractor has to be more salient in order to capture attention. We tested this prediction using an empirical and modeling approach of the visual search distractor paradigm. For the empirical part, we manipulated salience of target and distractor parametrically and measured reaction time interference when a distractor was present compared to absent. Reaction time interference was strongly correlated with distractor salience relative to the target. Moreover, even distractors less salient than the target captured attention, as measured by reaction time interference and oculomotor capture. In the modeling part, we simulated first selection in the distractor paradigm using behavioral measures of salience and considering the time course of selection including noise. We were able to replicate the result pattern we obtained in the empirical part. We conclude that each salience value follows a specific selection time distribution and attentional capture occurs when the selection time distributions of target and distractor overlap. Hence, selection is stochastic in nature and attentional capture occurs with a certain probability depending on relative salience.

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Introduction

Visual attention can be allocated in a stimulus-driven (bottom-up) or an observer-guided (top-down) fashion [1], with both sources of control combining to determine which location or object in the field is attended. The process of selection often is investigated in the realm of visual search. In this paradigm, the task is to find a pre-defined target among distractors and (depending on the task) indicate its presence or absence or make another decision based upon its features. Attentional selection in the search process has been subject to a variety of experimental studies [2–5] as well as computational models [6–10].

A variant of the visual search paradigm that permits attentional selection to be investigated precisely is the visual search distractor paradigm [11,12]. In this paradigm, a task-relevant target singleton and an irrelevant distractor singleton (both carrying unique features compared to all other stimuli) are surrounded by homogeneous non-target stimuli. An example would be a display containing a predefined target, a grey tilted bar, and a distractor, a colored vertical bar, amongst grey vertical non-target bars. The task is to find the target while ignoring the distractor. Typically, the item with the highest feature contrast is selected first or

'captures attention' initially, as evidenced by reaction time (RT) interference (for distractor-present compared to -absent trials) when the distractor is characterized by a higher feature contrast (relative to the non-targets) than the target [3,11–16], but not when it has a lower feature contrast [11–13]. On this basis, it has been claimed "that the initial shift of attention [is directed] to the most salient singleton" [3] and "that the bottom-up salience signal of the stimuli in the visual field determines the selection order" [3].

In terms of functional architecture, stimulus-driven selection in visual search is thought to be mediated by an attention-guiding 'master' [17], 'activation' [6], or 'salience map' [18–20], which codes the physical distinctiveness of each location in the field in terms of its total feature contrast against the surrounding locations: the more a stimulus differs from those in its surround (e.g. a bar tilted by 45°, as compared to 7°, amongst vertical bars), the stronger its salience signal. A winner-take-all mechanism then selects that location on the salience map for focal-attentional allocation which exhibits the highest level of activation. In terms of the computations involved, existing models assume that after low-level feature extraction, a center-surround algorithm returns contrast images for each feature channel; these feature contrast maps are later combined to form the feature-independent salience

map, which serve as the basis for the attentional selection mechanism [18]. Although, in principal, attention is guided to the location with the highest activation, salience models typically assume noise to influence some stage(s) of salience computation [19,20]. Noisy coding turns selection into a stochastic process: the more salient the target, the higher the probability that it is the first item selected. The assumption of noise influencing attentional guidance is shared by prominent models of visual search [6,8,10,21].

Noise turns computed salience into a random variable with a certain distribution and an expected value. Consequently, these models require a differentiation of the concept of ‘*salience*’: salience may refer (i) to the expected value of the distribution of salience estimates, which corresponds to the distinctiveness of each item from its surround, as captured by contrast images or image statistics [22–24]; or (ii) to the actual outcome of the salience computation process on a given trial, which is subject to variability (due to noise) and can thus deviate from the expected value. To illustrate this differentiation, it is instructive to link salience-based selection to motion (direction) discrimination treated as a decision process [25]. Discrimination of motion direction within random dot kinematograms is a frequently used paradigm in the modeling of decisions [26]. Typically in this paradigm, some 100 dots are moving within a bounded area (some 3° of visual angle in diameter): a proportion of dots move coherently to either the left or the right, while the remaining dots have random trajectories. The observer’s task is to indicate the direction of the coherent motion. The decision model [25] presupposes the existence of motion-sensitive cells whose rate of firing is proportional to the coherence of motion in a specific direction. For the left versus right decisions, the relevant cells are those tuned to leftward and, respectively, rightward motion within their receptive fields. Hence, when a patch of dots is presented with a proportion of dots moving coherently e.g. to the right, signal detection models of this decision assume that the cells of both types exhibit activity, which is noisily distributed around different means. In particular, with rightward coherent motion in a random dot kinematogram, the activity induced in ‘right cells’ would be distributed around a mean value greater than that of the activity induced in ‘left cells’. The higher the proportion of coherently moving dots in the display, the farther apart the means of the two activity distributions are. A decision could be made by drawing one sample of evidence from the ‘left’ unit and one from the ‘right’ unit, choosing that direction which shows a higher level of evidence [27]. Decision models that do not only describe the outcome of decisions (as is the case with signal detection models), but also the distribution of decision times assume that the noisy activity of the motion-sensitive cells is integrated, or accumulated, over time. The output of this accumulation process, the decision variable, is constantly compared against a decision criterion, until the decision is made. That is, the noisy activity of motion detectors (e.g. in MT) is accumulated into a decision variable (presumably in the lateral intraparietal sulcus, LIP), based on which the decision is made.

We propose a similar logic for salience-based selection. Instead of two motion detectors for the two relevant directions in a random-dot motion discrimination task, we posit salience detectors for each location of visual space which are sensitive to feature contrast. These detectors have previously been assumed to be noisy. Instead of a signal detection theory-based decision, such as in Guided Search 2.0 [10], we propose that each detector’s activity is accumulated into a decision variable over time. All these decision variables are constantly compared against a criterion, with the first accumulator whose activity reaches the criterion leading to attentional selection of the respective location.

Accordingly, this model of selection does not only describe the outcome, but also the time course of selection decisions. That is, salience-based selection, rather than being taken to consist of the two successive steps, namely ‘salience computation’ followed by ‘attentional selection’, is considered as dynamic process in which a noisy signal is accumulated over time that triggers a selection decision.

Thus, as becomes apparent from the above considerations, there are two conceptually different notions of salience. The construct of physical feature contrast, which corresponds to motion coherence in the random dot kinematogram, is represented as sensory data by the activity of salience detectors in the brain (analogous to the activity of motion detectors representing motion coherence). This momentary neural representation is distributed around its mean, that is, it is a noisy signal. Because the expected salience value, that is the mean of the neural salience representation, is not linearly related to physical feature contrast [28,29], it needs to be estimated. This estimation is the intent of current salience models [22–24]. However, relevant for selection on a given trial is the accumulated signal of the neural representation, which is the decision variable. For clarity, in the remainder of the article, we refer to the concept of expected salience value as *stimulus salience* and the actual or accumulated estimate as *selection salience*, because the latter is the basis for attentional selection on a given trial. Stimulus salience is related to physical stimulus properties: for instance, a horizontal bar among vertical bars has a higher stimulus salience than a bar tilted by 30°. Solely based on the value of stimulus salience, focal-attentional selection would have to favor the horizontal bar. However, owing to noise in the computation process, the resulting estimates (i.e. selection salience) are distributed around the expected value of stimulus salience. Hence, if the distributions of selection salience for horizontal and 30° orientation contrasts overlap, first selection of the 30° bar is possible in principle: the selection salience of the 30° bar can be higher on a given trial than that of the horizontal bar. Stimulus and selection salience do not usually have to be differentiated in standard visual search (detection) tasks with only one salient target being present – because, despite noise, the stimulus salience distributions of target and non-targets virtually never overlap and the selection salience of a non-target can never be higher than that of the target. However, this differentiation becomes important when two conspicuous stimuli are presented, but only one is task-relevant: if selection salience is higher for the irrelevant (distractor) stimulus, even though its stimulus salience is lower than that of the relevant (target) item, it will nevertheless be attentionally selected first.

Thus, because of the noisy salience computation, in the distractor visual search paradigm, attentional capture would occur when the distractor has a higher selection salience than the target. A distractor can have a higher selection salience if its stimulus salience is higher, equal, or even lower compared to that of the target, depending on the overlap between the distributions of the target’s and the distractor’s selection salience. Consequently, (i) the occurrence of attentional capture would be proportional to the relative stimulus salience of the target and the distractor and (ii) distractors even less stimulus salient than the target would capture attention in a proportion of trials. This implies that if the proportion of attentional capture events is high, RT interference would be large; and if it is low, interference would be small.

Note, however, that this hypothesis has never been tested directly. Most studies of attentional capture have used only singleton distractors that were more salient than the target [14,30–33], and so cannot address this issue at all. On the other hand, there are a few studies that have contrasted (at most) two stimulus

salience conditions [11–13,34]. But even then, one cannot logically make any inferences about the stochastic dependency of selection (order) on stimulus salience (quite apart from the fact that interference effects heavily depend on the sample that is drawn from all possible stimulus salience values, that is the studies with two settings are likely to have contrasted only extreme, low and high, values of stimulus salience). In other words, although salience and visual search models assume noise in the selection process accounting for attentional capture by less stimulus-salient distractors, there is, to our knowledge, as yet no empirical evidence for this assumption. Testing this assumption would require varying the salience of targets and distractor parametrically, rather than (just) dichotomically.

On this background, the present study was designed to test the hypothesis of stochastic dependency between stimulus salience and attentional selection [10,21], using a combined approach of behavioral evidence and quantitative modelling [18–20]. In the behavioral part, we parametrically manipulated the stimulus salience of pop-out targets and pop-out distractors – so as to be able to (i) examine the occurrence of attentional capture across a greater range of stimulus salience values and (ii) determine the quantitative relationship between stimulus salience and attentional selection, that is, selection salience. For achieving these aims, it was necessary to quantify the difference in stimulus salience between targets and distractors – which we did by means of a visual search go/no-go *detection* task in which each of the pop-out stimuli, whether it served as a target or a distractor in the visual search *distractor* task, was presented as a single, to-be detected pop-out stimulus (i.e., without an irrelevant pop-out stimulus being present in the display). The detection RTs measured in this task served as estimates for stimulus salience. The difference in stimulus salience between a given target-distractor pair in the visual search *distractor* task was then quantified in terms of the difference in their associated detection RTs when they were presented alone in the visual search *detection* task. This procedure permitted us to compare stimulus salience across different dimensions.

Given that noise in the salience computation process turns attentional selection into a stochastic process, we expected (i) RT interference to be dependent on the relative stimulus salience and (ii) even less stimulus-salient distractors (compared to the target) to interfere, that is capture attention, in some proportion of trials. By contrast, if salience is not a random variable, as suggested by some authors [11,12], or noise is too small to affect attentional selection between two salient stimuli, attentional capture should occur only with distractors more stimulus-salient than the target. In order to verify that RT interference by less salient distractors is indeed caused by attentional capture, we recorded eye movements in an additional experiment with distractors less salient than the target.

As a second step, we computationally modeled the results of the behavioral visual search distractor experiment; specifically, we modeled selection salience in the distractor paradigm based on the stimulus salience parameters estimated from the behavioral data in the detection task (see also [35]). The model we implemented is based on two-stage models of visual search, which assume that stimulus salience is computed spatially in parallel for all items in the display (stage 1) and then focal attention is allocated to the item with the highest selection salience value (stage 2). Note, that our model only describes the first step of this process: the salience-based decision as to what location in space attention should select. The second step, including attentional engagement and stimulus identification, is outside the scope of the present model. The only model that (to our knowledge) has made the distinction between stimulus salience and selection salience explicit is Guided Search [10]. GS assumes that the selection salience value is stochastically

related to stimulus salience, that is pre-attentive salience coding for each item in the display is subject to noise, necessitating a signal-detection-type decision [36] as to which item to transfer to the second, focal-attentional processing stage. Signal detection models, in general, account for response proportions, such as those of hits and false alarms, but not for the temporal duration of the underlying decisions. Likewise, GS makes statements only about the proportion of selection decisions directed to the target versus to a non-target, but not the time-course with which the decisions are made. However, pop-out targets can differ in the speed with which they are singled out, that is they can be equivalent in terms of selection proportion (the target is always selected first), but differ in the time it takes until the item is selected. Behaviorally, it has been demonstrated that targets that pop out (i.e., that have flat RT/set-size functions) can differ in detection RTs [37–40]. For example, among vertical bars, both a target tilted by 45° and one tilted by 12° pop out, but differ in their associated detection RTs. Töllner, Zehetleitner, Gramann, and Müller [41] demonstrated that such differences in RTs are indeed attributable to differences in selection times: the latency of the so-called N2pc component of the EEG, which is assumed to reflect the transition from pre-attentive to post-selective stimulus processing [42,43], increased as a function of decreasing stimulus salience of the pop-out target. Given this finding and the notion that a selection decision is based on the accumulated sensory evidence [25], we considered it important to take into account the time course of selection decisions in our model; that is, we simulated the data of the visual search distractor paradigm in a new model of salience-based selection that assumes a time course of selection decisions and thus permits the proportion of capture trials to be predicted for a given salience difference (derived from the respective detection RTs) between target and distractor.

In summary, the present study had two goals, one empirical and one theoretical. Empirically, it was designed to test two central predictions of visual search and salience models: in a distractor paradigm, (i) RT interference should be proportional to the difference in stimulus salience between target and distractor, and (ii) interference should also be observed with distractors less stimulus-salient than the target. Furthermore, assuming that this RT interference is actually caused by attentional capture (rather than some filtering cost [44]) less stimulus-salient distractors should also be found to capture the eyes. Theoretically, the study was intended to computationally model the conceptual distinction between stimulus salience (as estimated by RTs in a search detection task without distractors) and selection salience, the noisy estimate of stimulus salience computed by the pre-attentive visual system. To this end, the data of the behavioral visual search distractor experiment were modeled, based on the behaviorally estimated stimulus salience parameters. The model makes predictions about which item is selected first, rather than about RT interference.

Behavioral Reaction Time Experiment

Methods

Ethics statement. Participants gave their written informed consent. The study was approved by the ethics committee of the Department of Psychology, LMU Munich, in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

Participants. Fifteen paid (€ 16) volunteers, with a median age of 27 (range 20–50) years, five of them male, all dextral and with visual corrected-to-normal acuity, participated in this study.

Stimulus presentation and data acquisition. The experiment was conducted in a sound-insulated room, and was controlled by a program purpose-written in C++. Stimuli were presented on a 19" View Sonic Graphics Series G 90 fB monitor at a resolution of 1,024×768 pixels and a refresh rate of 85 Hz; viewing distance was approximately 57 cm. Participants responded using their left and right index fingers, respectively, to press one of two vertically arranged buttons on a purpose-built response pad. RTs and response accuracy were recorded online.

The display consisted of 39 vertical broken grey bars presented on black background and arranged on three imaginary concentric circles (1.88°, 3.25°, and 4.63° of visual angle in radius, with 8, 12, and 18 bars, respectively) around the center of the screen, which was occupied by another bar. Bars were 0.25°×1.13° in size and had a 0.13°-gap randomly located at the top or the bottom of each bar. Targets differed from non-targets in orientation (7, 8, 9, 14 and 45° tilted from vertical), and distractors differed from non-targets in luminance (13.8, 14.8, 17.9, 19.4, and 25.5 cd/m² for distractors and 5.25 cd/m² for non-targets). A pilot experiment was conducted to ensure that target and distractor salience was sufficient for these stimuli to 'pop out' from the search array, that is, their associated detection times were independent of the number of non-targets in the display (see Text S1 and Table S1).

Design and procedure. Two 1-hr sessions were carried out on consecutive days, at the same time of day. The first part of each session was the distractor experiment; the second part was a post-experiment for stimulus salience measurement (for the latter, see *Baseline salience measurement*). The within-subject design of the distractor experiment was 2 (distractor present vs. absent)×5 (target salience)×5 (distractor salience) factorial, resulting in 25 salience difference conditions. A target was present on all trials; a distractor occurred randomly in 50% of the trials. Target and distractor were placed randomly at the 12 possible positions on the second circle to keep eccentricity constant. All salience difference conditions were presented in random order within blocks. Participants completed 20 blocks of 50 trials each day, yielding a total of 2,000 trials and 40 trials per salience difference condition.

Each trial started with a white fixation dot (radius=0.05°) presented for a duration uniformly distributed between 900 and 200 ms, that was superseded by the search display which remained present until response (Figure 1A). Participants were instructed to indicate, as quickly and accurately as possible, the gap location (top or bottom) of the target by pressing the upper or lower button, respectively. In case of an error, visual feedback was provided, followed by an additional 500-ms blank screen before the next trial. At the end of each block, participants were informed about their mean RT and error rate.

Baseline salience measurement. Because salience is not linearly related to physical contrast [29], we used a behavioral measurement of salience, which was collected in a post-experiment after each session of the distractor experiment. Stimuli were the same as in this experiment. All target orientation and distractor luminance contrasts from the distractor experiment (Figure 1B) were presented as (to-be-detected) targets randomly intermixed with target-absent displays (as in the distractor experiment, targets never occurred on the outer circle). The design was 2 (target presence vs. absence)×2 (dimension luminance vs. orientation)×5 (contrast) factorial. Dimensions were blocked, contrasts were mixed within blocks. Participants' task was to indicate the presence of an orientation or luminance target via button press; response was to be withheld if no target was present. Four blocks consisting of 80 trials were performed each day, yielding a total of 640 trials and 32 trials per contrast condition. The stimulus display was presented until response or a maximum of 1,200 ms. Error

feedback was provided visually, immediately after the false response.

Using these detection RTs as our measure of stimulus salience, we calculated the salience difference between stimuli by subtracting distractor salience from target salience. For example, if a target was detected at a rate of 300 ms and a distractor at a rate of 400 ms, then their salience difference was -100 ms. Note that items of higher salience are associated with shorter RTs; negative salience differences indicate a distractor less salient than the target, and positive differences a distractor more salient than the target. This salience difference measure served as independent variable in the distractor experiment.

Data analysis. Only correct-response trials were used for analysis (distractor experiment: 96.5%; baseline salience measurement: 99.0%), excluding RTs shorter than 150 and longer than 1,500 ms in the distractor experiment (0.8%) and shorter than 150 and longer than 1,000 ms in the baseline salience measurement (0.2%). The first 20 trials (first 10 trials of the baseline salience measurement) of each session and the first 3 trials of each block served as practice trials and were also excluded from analysis. RT interference was calculated by subtracting mean RTs for target-only trials from mean RTs for target-plus-distractor trials. Statistical data analysis was carried out with R software [45]. Regression analyses were conducted with $n = 25$ salience difference conditions (aggregated across 15 participants); t-tests for RT interference of less salient distractors were conducted with $n = 15$ participants.

To test for the dependency of RT interference on relative salience between target and distractor, we used nonlinear least-square estimation for regression function fitting. The nonlinear function followed the form:

$$Y = \frac{a}{1 + e^{-\left(\frac{d-p}{g}\right)}}, \quad (1)$$

where a is the asymptote or maximum RT interference, d the salience difference, p the inflection point, and g the growth factor of the function.

Goodness of fit comparison of the regression functions was carried out using Bayes Information Criterion [46], which is calculated according to

$$BIC = -2 \log L + k \log n, \quad (2)$$

where L is the maximum likelihood of the data under the regression function, k the number of parameters to be estimated, and n the number of observations. Smaller BIC values indicate a better model fit.

Results and Discussion

We investigated the order of attentional selection in a distractor experiment with a unique, orientation-defined pop-out target present on all trials and a unique, luminance-defined pop-out distractor randomly interspersed in half the trials (Figure 1A; for stimulus pop-out characteristics, see Text S1 and Table S1). Target orientation and distractor luminance were manipulated such that the salience difference between the two items was varied parametrically in 25 steps (Figure 1B). Stimulus salience was estimated in a post-experiment (*Baseline salience measurement*) in which no distractors were presented and targets could be defined in the orientation or the luminance dimension. The times required to detect these targets served as salience estimates for the stimuli in the distractor experiment (Figure 2). We used the mean salience

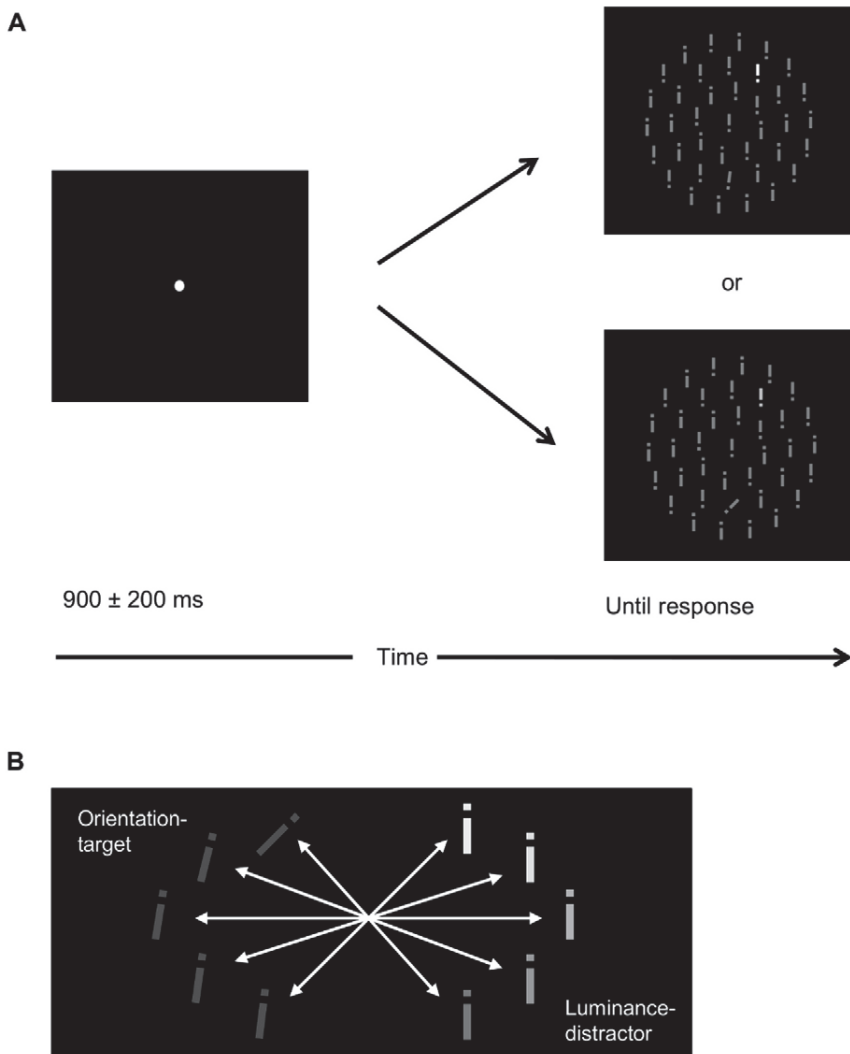


Figure 1. Experimental design and stimuli. (a) A search display, consisting of 39 broken grey bars arranged around three imaginary concentric circles, was presented in the center of the screen, on a black background. There was always an orientation target; and in half of the trials (randomly determined), there was also a luminance distractor. Each trial started with a white fixation spot that was hidden while the display was presented until response. Inter-stimulus-intervals varied randomly in the range 900 ± 200 ms. While ignoring a bright distractor, participants searched for a tilted target bar and decided, via a speeded button press, whether the gap was located at the top or the bottom of the bar. This response decision required focal attention to be allocated to the target. (b) 25 Saliency difference conditions resulted from 5 orientation (7, 8, 9, 14, 45°) and 5 luminance (13.8, 14.8, 17.9, 19.4, and 25.5 cd/m^2) contrasts. doi:10.1371/journal.pone.0052595.g001

difference values of all participants to predict RT interference on distractor-present, compared to distractor-absent, trials using nonlinear regression functions. RT interference in this task is commonly attributed to automatic prior selection of the distractor, and absence of interference to direct selection of the target [12].

Figure 3A presents the observed RT interference (for correct-response trials), averaged across participants (mean RT [\pm SEM] on distractor-present trials = 660 [± 12.9] ms; mean RT interference = 28 [± 4.4] ms), for luminance-defined distractors and orientation-defined targets as a function of their saliency difference. RT interference was strongly correlated with the saliency difference ($n = 25$; Pearson's $r = .91$ [$t(23) = 10.8$, $p < .001$]), indicative of the order of selection ('target first') being dependent on relative object saliency. This relationship already exhibits the expected characteristics: (i) the magnitude of interference varies with the saliency difference between target and distractor, and (ii)

distractors considerably less salient than the target do interfere with search.

Next, we fitted two nonlinear regression functions to the data, one with the inflection point free to vary (R_1) and one in which it was fixed to 0 ms saliency difference (R_2). We then compared the functions' goodness of fit by examining their Bayes Information Criterion values [46], where smaller *BIC* values indicate a better fit. Regression function R_1 yielded an asymptote of 73 ms, an inflection point of 7 ms, and a growth factor of 29 ms. For the nonlinear regression function R_2 , where the inflection point was set to 0 ms, the RT interference asymptote was estimated to be 67 ms, and the growth factor to be 26 ms saliency difference. *BIC* value comparison confirmed regression function R_2 (with the inflection point set to 0 ms) to fit the data better than R_1 ($BIC_{R1} = 178$ vs. $BIC_{R2} = 175$; see Table 1 for details).

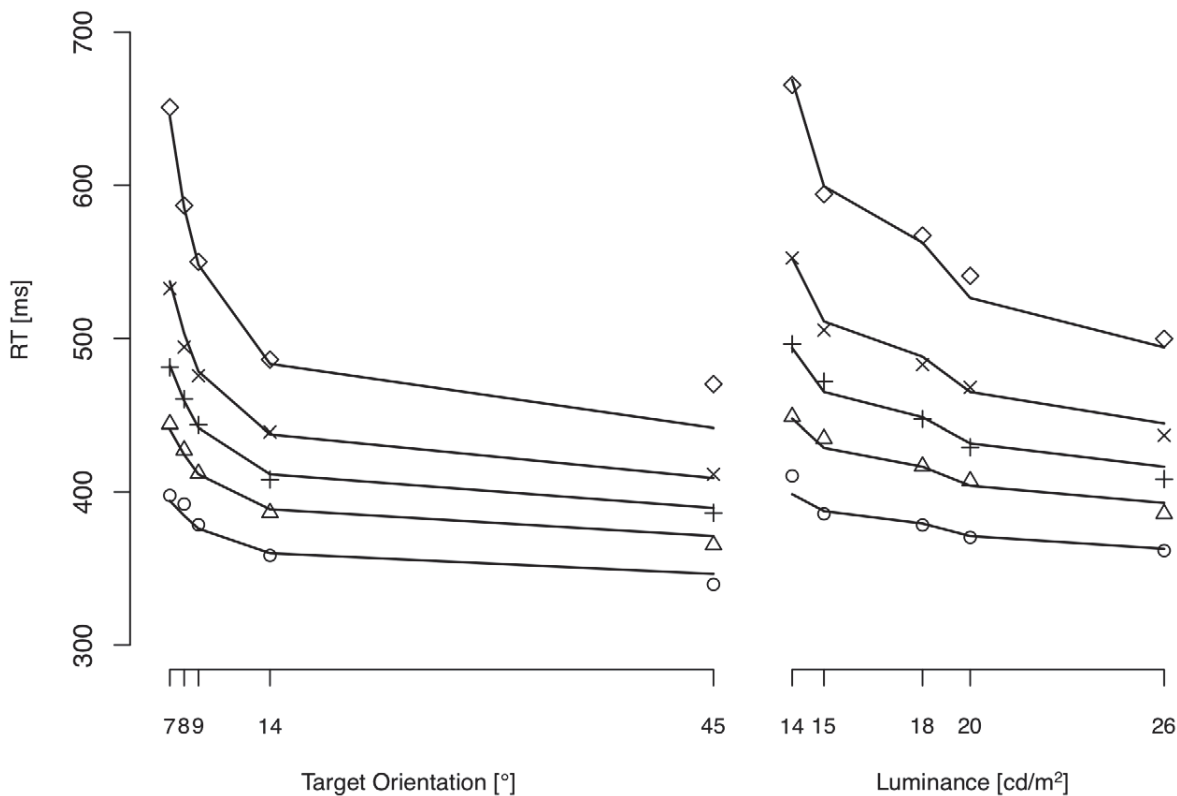


Figure 2. Empirical data of the baseline salience measurement and data fitted by the accumulator salience model. Left panel: five salience levels of orientation targets. Right panel: five salience levels of luminance targets. Symbols depict RT quantiles of each condition as follows: o = .1, Δ = .3, + = .5, × = .7, and ◇ = .9. Lines represent RTs generated by the model. Fitted RTs differ from empirical RTs by 5 ms on average (range: 0 to 28 ms). Additional parameter estimates were $T_{er} = 300$ ms, $s_{er} = 70$ ms, $a = .08$, and $\beta = .294$. doi:10.1371/journal.pone.0052595.g002

These results argue in favor of a proportional first selection of the distractor dependent on its salience difference to the target. The function where the inflection point was set to 0 ms indicates that equally salient targets and distractors are equally likely (50%) to be selected first. First-selection probability for a given item then increases as its relative salience increases. The shift of the inflection point into the positive range in regression function R_I indicates that at the point at which selection probability is equal for both items, the target is actually less salient than the distractor (rather than the two stimuli being equi-salient). This might reflect an influence of top-down control, permitting the target to compensate for this discrepancy in relative salience. However, reconsidering our measure of relative salience, it is possible that target and distractor salience is not the same in the distractor experiment as measured in the baseline salience measurement. There are three possibilities of how they may differ between tasks. First, if a stimulus is presented alone as in the baseline salience measurement, the display is more homogeneous compared to when an additional distractor is presented – in which case salience might be overestimated in the baseline salience measurement relative to the distractor experiment. However, because this would apply to both the target and the distractor, this should not affect relative salience in the distractor experiment. A second reason for diverging relative salience in the distractor experiment derives from the fact that stimulus salience was measured after the distractor experiment. One might argue that assigning the role of target to the orientation dimension (and that of distractor to the luminance dimension) in the distractor experiment induces ‘priming’ for orientation-defined

singletons, resulting in an overestimation of target salience and an underestimation of distractor salience in the subsequent baseline salience measurement. The implication is that at 0 ms salience difference, the distractor would actually be more salient than the target and the true point of equal salience would lie in the negative range of salience differences. However, according to Maljkovic and Nakayama [47], priming effects for the orientation dimension, as an aftereffect of having been assigned the target role in the distractor experiment, should dissipate within a few trials in the baseline salience measurement. Third, stimulus salience might be different in the distractor experiment because of top-down weighting [48–51]. When both stimuli are presented together, as in the distractor experiment, the weight of the target might be up-modulated and that of the distractor down-modulated. That is, the salience values determined in the baseline salience measurement would be under-estimates for targets and over-estimates for distractors. If this was the case, true equality of salience should be in the positive range of salience differences and the distractor would be even less salient than the target at the point of 0 ms salience difference. To test for the latter two possible types of salience estimation errors, we fitted regression functions with varying inflection points from -10 to 15 ms salience difference and calculated the corresponding BIC 's. As figure 4 shows, BIC was lowest for a regression function with the inflection point in the positive range of salience differences. This implies that at 0 ms salience difference, in the distractor experiment, the distractor is still less *stimulus-salient* than the target and top-down weighting shifts the point of equal salience difference into the positive range.

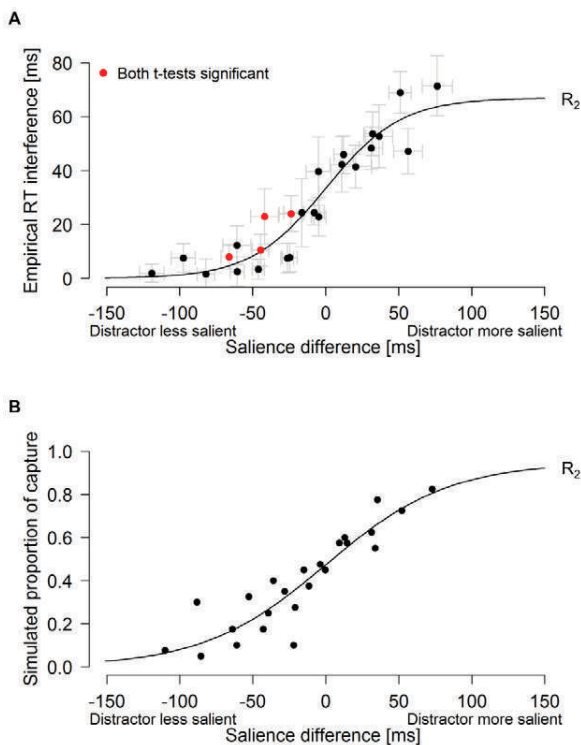


Figure 3. Behavioral interference and modeled proportion of capture as a function of salience difference. (a) Empirical RT interference, averaged across participants, represents the RT difference, in ms, between distractor-present and distractor-absent trials. Salience difference, averaged across participants, was derived from detection times in the baseline salience measurement requiring a simple target-present vs. target-absent decision (see *Methods of Behavioral reaction time experiment*). Negative x-values indicate distractors less salient, and positive x-values distractors more salient than the target. Dots represent mean values of RT interference for each salience difference condition ($n=25$); arrows indicate the associated standard errors. Red dots indicate significant RT interference by distractors significantly less salient than the target (t -tests: $p<.05$). Solid curve: regression function curve R_2 . (b) Proportion of capture in the distraction experiment was predicted by salience difference, derived from fitting empirical salience difference values. Again, dots represent mean values of RT interference for each salience difference condition ($n=25$). The curve depicts the nonlinear relationship according to R_2 . doi:10.1371/journal.pone.0052595.g003

Consequently, our measure of salience difference is rather conservative, that is RT interference by less salient distractors is actually even higher than we have assumed here.

The nonlinear regression function already implies that distractors less salient than the target do interfere with search. To examine RT interference by less salient distractors more closely, we conducted t -tests for all salience differences for which the distractor was significantly less salient (criterion of 0 ms salience difference) than the target. These tests confirmed there are indeed distractors less salient than the target that produced significant RT interference (Figure 3A).

Overall, the findings of RT interference being sigmoidally related to relative salience and of less salient distractors capturing attention, are compatible with visual search and salience models [10,18–24] that assume that the salience coding and, thus, the selection process is subject to internal noise.

Table 1. Parameter estimates of the model predictions fitted to empirical and modeled data.

Variable	Unstandardized estimate	S.E.	t	p	CI	BIC
<i>Human data</i>						
R_1						178
Asymptote	73		9.66	7.53	.001	58–117
Inflection point	7		10.26	0.65	.263	–10–48
Growth factor	29		5.79	5.79	.019	18–47
R_2						175
Asymptote	67		2.90	23.09	<.001	61–73
Inflection point	0					
Growth factor	26		3.39	7.57	<.001	19–34
<i>Model data</i>						
R_2						–42
Asymptote	0.95		0.04	24.87	<.001	0.87–1.03
Inflection point	0					
Growth factor	42		5.01	8.39	<.001	32–55

Note: $n=25$. Estimate for empirical data in ms; asymptote estimate for modelled data in proportions. R_1 = Nonlinear regression function. S.E. = Standard Error. t and p = value and probability of the t statistic associated with parameter estimate. Degrees of freedom: R_1 : 23, R_2 : 22. CI = 95% confidence interval. BIC = Bayes Information Criterion. doi:10.1371/journal.pone.0052595.t001

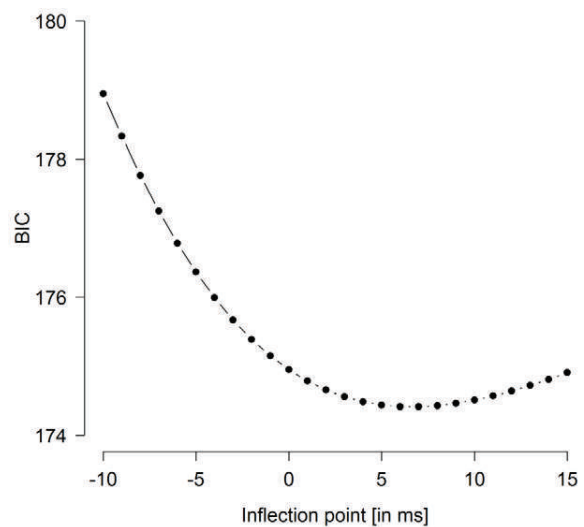


Figure 4. Course of BIC dependent on the inflection point of the regression function. Regression functions were fitted according to formula (1), with the inflection point as fixed parameter. Inflection points are specified in ms of salience difference. doi:10.1371/journal.pone.0052595.g004

Computational Model

A second, theoretical goal of the present study was to develop and test a computational model of how stimulus salience translates into selection salience, that is, a model accounting for the variation in the outcome of the selection process based on stimulus salience – concretely by simulating the data of the distractor paradigm.

Importantly, the model we devised makes predictions about the item that is selected first (rather than directly about RT interference) and takes noise and the time course of selection, based on stimulus salience, into account. Selection is assumed to involve a decision between all stimuli in the display and the dynamics of selection processes to be stochastic in nature [10,19–24], with the outcome being dependent on stimulus salience and a noise component.

In more detail, the model assumes that the salience map develops over time probabilistically (Figure 5). Each item in the visual scene is represented by a sensory-evidence accumulator unit, the drift rate of which corresponds to stimulus salience. Accumulation is assumed to be a leaky and noisy process [52]. That is, sensory evidence does not accumulate infinitely, but comes to settle eventually around an asymptotic value (mathematically the proportion of the drift rate to leak). A selection decision is triggered as soon as sensory evidence for a specific location exceeds a threshold. In this model, stimulus salience determines the drift rate with which sensory evidence is accumulated, and selection salience is the accumulating, or accumulated, sensory evidence. In contrast to this dynamic process, which is continuous over time, conventional models of visual salience essentially envisage a snapshot-like topographic representation of the (physical) feature contrasts present in the scene, which serves as the basis for selection decisions: the location of maximum contrast is attentionally selected by a winner-take-all mechanism, the time course of which is usually not modeled explicitly.

For simulating the results of the distractor experiment, in a first step, we fitted the model to the empirical baseline salience measurements in order to obtain parameter estimates for stimulus salience; in the next step, these parameters were used to simulate selection salience in terms of the probability of a distractor versus a target being selected first.

Methods

We implemented the selection salience map using leaky accumulators [52]. That is, all items on the screen are represented by leaky accumulators that race against each other for selection; the item that first exceeds a threshold criterion is then selected. Model parameters are drift rate v , leakage β , and threshold a . At each time step, sensory evidence of accumulator I is updated according to the formula:

$$dx_i = [v_i - \beta x_i]h + N(0, \sigma)\sqrt{h}, \tag{4}$$

where h is the step size, which is set to 1 ms in the model fits, and $N(0, \sigma)$ denotes a Gaussian distribution with mean 0 and standard deviation σ . Within-trial variability is normally distributed with $\sigma = 0.1$. Salience computation terminates as soon as one accumulator exceeds the selection threshold, resulting in a decision time of attentional selection (t_{sel}). Observed reaction time is usually considered to be the sum of decision time and time of non-decision-related processes such as basic encoding time between retina and primary visual cortex as well as the time necessary after the decision has been made for the motor commands to be transmitted to and innervate the effector muscles. Non-decision times (denoted T_{er}), which incorporate the time necessary for stimulus encoding and response production, are usually assumed to be distributed uniformly [53] with range s_{er} . Note that, potentially, the model could also be turned into a winner-take-all ‘network’ by adding lateral inhibition between each accumulator. In this case, over time, there would eventually be only one

accumulator active, with the activities of all other accumulators driven to (near-) zero. As concerns the selection times for the first item, the main question at issue in the present study, such a model would yield similar results.

In pop-out search, accumulators for non-target stimuli can be left out of the simulation, because non-targets are effectively never selected – as evidenced by search time for pop-out targets being independent of the number of non-targets [38]. That is, for the baseline salience measurement, in which only a target (but no distractor) was presented amongst the non-targets, the selection salience map model is reduced to one accumulator racing towards its threshold. In the distractor experiment, by contrast, a pop-out target and a pop-out distractor were presented simultaneously. In the model, this is represented by two accumulators racing against each other, with the drift rates of the two accumulators corresponding to target and distractor stimulus salience, respectively.

The simulation proceeded in two steps: first, the model described above was fit to the data of the baseline salience measurement to obtain drift rates corresponding to the different levels of stimulus salience induced by the 10 possible ‘targets’, as well as estimates of the other parameters (β , a , T_{er} , and s_{er}); second, these estimated parameters were then used to simulate the proportion of capture trials in the distractor experiment.

From the empirical data of the baseline salience measurement, RT distributions were characterized by the .1, .3, .5, .7, and .9 quantiles. These were calculated per observer per condition and then pooled across all observers [53]. Model parameters consisted of one selection threshold a , leakage β , non-decision time T_{er} and its range s_{er} , and additionally one drift rate v_i per salience condition. For each parameter set, 50,000 replications of the random walk process were simulated (see equation 4); that is, for each salience condition, the model produced 50,000 model RTs. From these, the model .1, .3, .5, .7, and .9 quantiles as well as the error rates were computed. An error was recorded if the accumulator failed to reach the selection threshold within 1,200 ms (as in the empirical experiment). For each parameter set, the weighted least squares (WLS) was calculated according to

$$4(pc_{th} - pc_{ex})^2 + \sum_i w_i pc_{ex} [Q_{th}(i) - Q_{ex}(i)]^2, \tag{5}$$

where pc stands for percent correct and the indices th and ex denote the modeled (*theoretical*) and empirically measured (*experimental*) statistics, respectively; $Q(i)$ signifies the .1, .3, .5, .7, and .9 quantile RTs, and w_i is a weight which was set to 2 for the .1 and .3 quantiles, to 1 for the .5 and .7 quantiles, and to 0.5 for the .9 quantile [54]. That is, the squared differences between empirical and model percent-correct scores and, respectively, empirical and model quantiles are calculated, and the latter differences are weighted more strongly for lower than for higher quantiles, because estimates for higher (especially the .9) quantiles are more variable than those for ‘faster’ quantiles. A Nelder-Mead simplex optimization algorithm [55] implemented in R [45] was used to minimize the WLS cost function. The fitting procedure commenced with manually selected starting variables and was run for 200 iterations ten times in a row, each time using the optimization result from the previous run as starting values for the next run in order to avoid local minima. Local minima are likely to be avoided by this procedure, because during the simplex optimization, the step sizes with which the parameter space is sampled become adaptively smaller. When restarting the algorithm, the step size is increased again, thus providing the potential for escaping from a

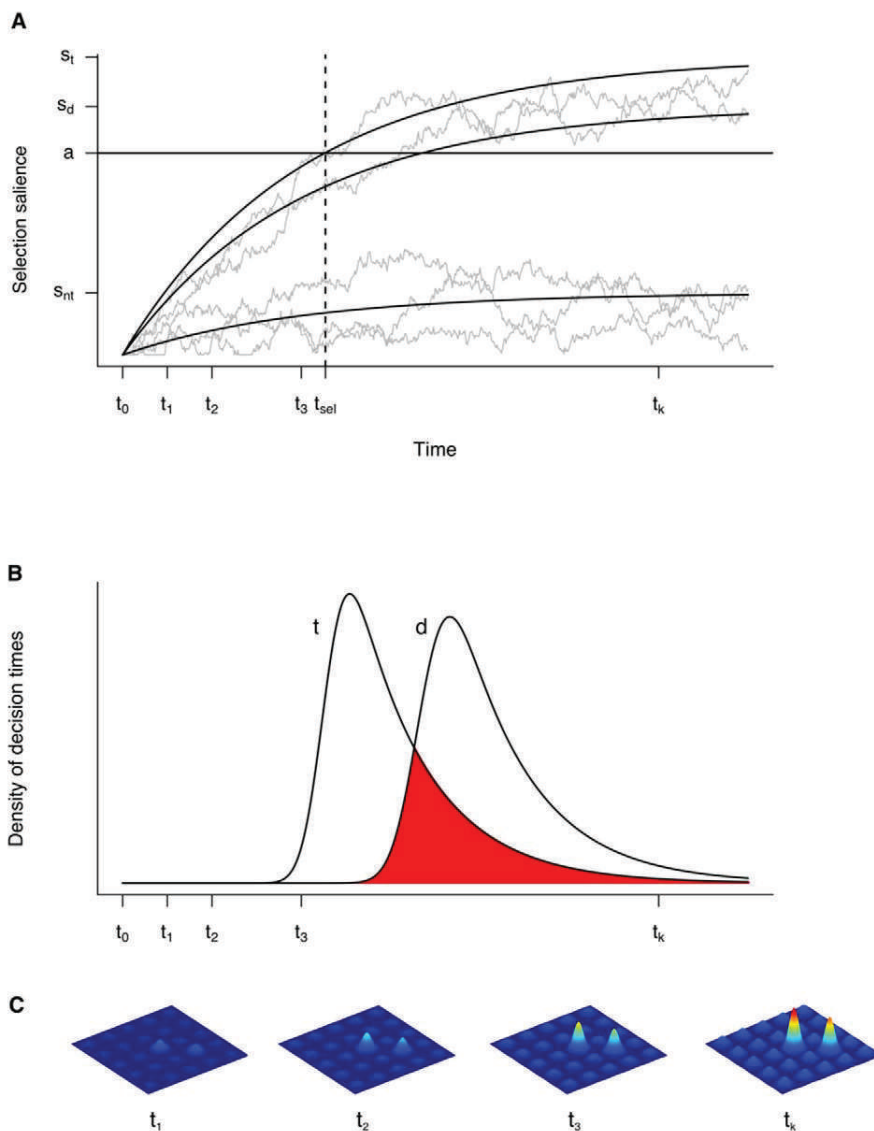


Figure 5. Stochastic model of salience-based selection. (a) For each location in the visual field, salience is accumulated over time $t = \{t_1, t_2, \dots, t_k\}$ by leaky accumulators. Gray jagged lines represent sample paths of sensory evidence accumulation over time, influenced by noise. Mean accumulation behavior is indicated by solid black lines. Salience asymptotes s (s_t = target salience, s_d = distractor salience, s_{nt} = non-target salience) indicate maximum salience when time is infinite and noise absent; asymptotes correspond to the salience values of map locations computed by deterministic models. (b) Selection time distributions (t = target, d = distractor) indicate selection time variation due to noise. Overlap of these distributions (red area) marks the range within which a distractor may be selected first even if it is less salient than the target. (c) The final salience pattern evolves over time, as illustrated by heat maps at different points in time.
doi:10.1371/journal.pone.0052595.g005

local minimum [56]. Finally, the optimization procedure was run with maximally 5,000 iterations to yield the final set of parameters.

Those parameters which fitted best to the baseline salience measurement data were then used to simulate capture in the distractor experiment. The model was based on the assumption that in cases of both, a target and a distractor being present, two accumulators race against each other for selection, one with a drift rate corresponding to target stimulus salience and the other with a rate corresponding to distractor stimulus salience; the accumulator which first reaches the selection threshold wins the race. Capture was then operationalized as the proportion of trials in which the distractor accumulator completed the race before the target accumulator. For each combination of target and distractor, the

selection threshold a , the leakage β , and the two salience values were taken from the fit of the baseline salience measurement data and 40 races were simulated (the same number of trials as were used in the empirical study).

Results and Discussion

As RT interference is an indirect measure of the order of attentional selection, the underlying mechanism can only be inferred. Therefore, to strengthen our hypothesis about the relationship between salience and order of selection, we computationally implemented the proposed salience-based selection mechanism (Figure 5), estimated target salience from the (behavioral) baseline salience measurement, and simulated inter-

ference for the distractor experiment. RTs generated by the salience model yielded a close fit to the empirical RT distributions (Figure 2) for the various orientation and luminance targets in the baseline experiment: reduced salience slowed search and increased the spread of the RT distributions. The goodness of fit is remarkable given that across the ten different target conditions, only one parameter (the drift rate, corresponding to salience) was free to vary, whereas the parameters a (selection threshold), β (leakage of the accumulator), T_{cr} (non-decision time), and s_{cr} (variability of T_{cr}) were kept constant.

Importantly, when simulating the data of the distractor experiment using the fitted parameters from the baseline salience measurement, the predicted proportions of capture were similar to the observed RT interference (Figure 3B): the salience model simulates distractors less salient than the target to capture attention, the proportion of capture events to depend sigmoidally on salience difference, and capture to occur in half the trials with distractor of equal salience relative to the target. This qualitative similarity is reinforced by comparing the fits of nonlinear regression function R_2 to the simulated and the empirical data: the inflection point and growth factor parameters of the nonlinear fits did not differ, as indicated by the overlapping confidence intervals (see Table 1). Keeping the leakage parameter β constant at zero does not qualitatively alter the fit of the baseline experiment or the proportions of interference. However, there are two conceptual arguments for assuming leakage. First, without leakage, evidence would accumulate towards infinity over time, which is implausible with respect to the limitedness of neuronal firing rates. Second, with leakage, sensory evidence averages to an asymptote which is proportional to the salience values calculated by conventional, 'static' salience algorithms.

Behavioral Eye Movement Experiment

Although RT interference has been attributed to attentional capture in most previous studies [11–13,15], there is also the possibility that RTs are slower on distractor compared to target-only trials not because attention is first captured by the distractor, but because the distractor draws on the same processing resources as the target and thus slows target selection. Conceivable mechanisms of slowing are filtering [57] or competitive interactions [58] to be resolved in favor of the target. Whatever the precise mechanism that may underlie such slowing effects, in the present context, the critical question is whether or not the RT interference produced by distractors less salient than the target is the result of attentional capture. Empirical RT data cannot answer this question (RT interference may be caused by slowing, attentional capture, or both), and although our modeling results demonstrate that a capture account could explain the pattern of RT interference effects, it does not rule out alternative accounts in terms of non-capture slowing. Given this, we examined for attentional capture of the eye by (less salient) distractors in an eye-tracking experiment. Involuntary capture of the eye by a distractor is commonly taken as a strong indicator of attentional capture [59]. Accordingly, the finding of oculomotor capture would corroborate attentional capture as a source of RT interference. In the eye-tracking experiment, participants' task was to make a direct saccade to the target, while a less salient distractor could be present in the display.

Methods

Methods were the same as in the RT distractor experiment, unless stated otherwise.

Participants. Eight paid (€ 8) volunteers, with a median age of 23 (range 20–39) years, one of them male, seven dextral, and with visual corrected-to-normal acuity and normal color vision, gave written informed consent to participate in this experiment.

Stimulus presentation and data acquisition. Stimuli were generated using a ViSaGe system (Cambridge Research Ltd., UK) with a purpose-programmed Experimental Toolbox for MATLAB (The MathWorks, Inc.). Stimulus displays were presented on a 22-inch Mitsubishi Diamond Pro 2070SB CRT monitor with a screen refresh rate of 120 Hz and a screen resolution of 1,024×768 pixels. Eye movements were recorded at a sampling rate of 1000 Hz by means of an EyeLink 1000 Desktop Mount eye tracker (SR Research Ltd., Canada) positioned below the display monitor. Participants viewed the monitor from a distance of about 70 cm; to minimize head movements, a chin and forehead rest were used. Eye movements were recorded from the right eye; however, stimulus displays were viewed binocularly.

Grey vertical bars (without gaps) of $0.25^\circ \times 1.35^\circ$ of visual angle were arranged on three imaginary concentric circles (2° , 4° , and 6° of visual angle in radius, with 6, 12, and 18 bars, respectively). Targets differed from non-targets in orientation (22° tilted from vertical, randomly to the right or left), and distractors differed from non-targets in color (distractor 1: 180/100/106, distractor 2: 171/104/110 RGB). All stimuli were matched for luminance.

Design and procedure. The experimental session started with the eye-tracking experiment, after which the baseline salience measurement was conducted. The eye-tracking experiment implemented a 2 (distractor absent vs. present)×2 (distractor salience) factorial within-subject design, with two salience difference conditions. To ensure reliable differentiation between target and distractor fixations for the data analysis, distractor positioning was restricted in the following way: the target position was chosen randomly out of the 12 possible positions on the middle circle; the distractor position was then chosen to be shifted by three or five positions to either the left or the right from the target position (each in a random 25% of the distractor-present trials). There were 80 trials per salience condition. This resulted in 320 trials overall, which were presented in 4 blocks of 80 trials each. All salience difference conditions were presented in random order within blocks.

The task was to make a speeded saccade to the target. Observers were instructed to fixate the fixation cross at the trial start until the appearance of the search display, and then to make a direct saccade to the (orientation) target, while ignoring the (color) distractor. In case the first saccade went nevertheless to the distractor, participants were instructed to direct the next eye movement to the target. In addition, they were told that after having made a saccade to the target, they should fixate it until the disappearance of the search display.

Each trial started with a fixation cross ($0.5^\circ \times 0.5^\circ$) for 1,000 ms. Then, the search display appeared and remained visible for 1,000 ms. The intertrial interval, in which a black (blank) screen was displayed, was of a random duration between 700 ms and 1,100 ms. Observers were encouraged to use this interval for briefly closing and resting their eyes, so that they could minimize blinks during the subsequent trial. Additionally, participants could take short breaks between experimental blocks. Prior to each block of trials, a nine-point calibration of the eye tracker was conducted.

Baseline salience measurement. Salience measurement was the same as for the reaction time experiment, unless stated otherwise. Apparatus and stimuli were the same as in the eye-tracking experiment, that is, the to-be-detected targets were either 'oriented' or 'colored'. Six blocks consisting of 40 trials were performed, yielding a total of 240 trials and 40 trials per target

condition. Each trial started with the presentation of a white fixation cross ($0.5^\circ \times 0.5^\circ$) for a random duration ranging from 700 ms to 1,100 ms. Thereupon, the search display was presented and remained visible until response or a maximum duration of 1,000 ms.

Data analysis. For the analysis of the baseline salience measurement, error trials (0.9%) and target-absent trials were excluded. In addition, RTs shorter than 150 ms and longer than three standard deviations above an observer's mean per target type were discarded as outliers (0.8% of all trials). For the analysis of the eye-tracking data, trials were excluded on which search display onset occurred during a saccade or the eye-tracker failed to track the observer's pupil (4.3%). Saccade latencies were calculated as the time between onset of the search display and the initiation of the observer's first saccadic eye movement. Trials with initial saccade latencies below 80 and above 600 ms were excluded (2.9%). The remaining data underwent a drift correction: Before the onset of the search display (i.e. at the end of the fixation cross display), gaze was assumed to have rested on the fixation cross. Thus, for drift correction, the eye's deviation from the fixation cross was subtracted from the subsequent gaze position data for this trial. The initial saccade after search display onset was then assigned to the target or the distractor if it landed within 3° of visual angle of the respective (target or distractor) location. Initial saccades that went neither to the target nor to the distractor were not included in the subsequent analysis (2.8% of the remaining trials).

Salience difference, which again served as independent variable, was computed as in the RT distractor experiment. To ascertain that each distractor was less salient than the target in the baseline experiment and whether the percentages of distractor fixations were greater than zero in the eye-tracking experiment, one-sided t-tests were calculated on the sample of eight participants.

Results and Discussion

The eye-tracking experiment was designed to examine whether the interference by less salient distractors observed in the RT distractor experiment was the result of attentional capture; participants' task in this experiment was to make a speeded saccade to the orientation-defined target, while a color-defined, but less salient distractor could be present at the same time. Distractor color was manipulated in two steps. As in the RT experiment, stimulus salience was estimated in a post-experiment (*baseline salience measurement*). The times required to detect these (orientation- and color-defined) stimuli served as salience estimates for the stimuli in the eye-tracking experiment.

Detection times were significantly faster for the orientation target ($M = 376$ ms, $SD = 37$) compared to both color distractor 1 ($M = 399$ ms, $SD = 54$; $t[7] = -2.1$, $p < .05$) and color distractor 2 ($M = 414$, $SD = 54$; $t[7] = -3.3$, $p < .01$). Hence, both distractors were considerably less salient than the target.

For the eye-tracking experiment, we calculated mean percentages of target and distractor fixations (based on distractor-present trials) for the two distractor types. Figure 6 presents these as a function of the salience difference between target and distractor. With color distractor 1 (salience difference of -24 ms) in the display, 22.5% of the initial saccades went to this distractor rather than to the target. With color distractor 2 (salience difference of -39 ms), there were 13.3% oculomotor capture trials. The capture rate was significantly above zero for color distractor 2 as well as for color distractor 1 ($t[7] = 5.1$, $p < .001$ and, respectively, $t[7] = 5.7$, $p < .001$). Thus, even though both color distractors were less salient than the target (as established in the baseline salience measurement), they led to a considerable amount of capture

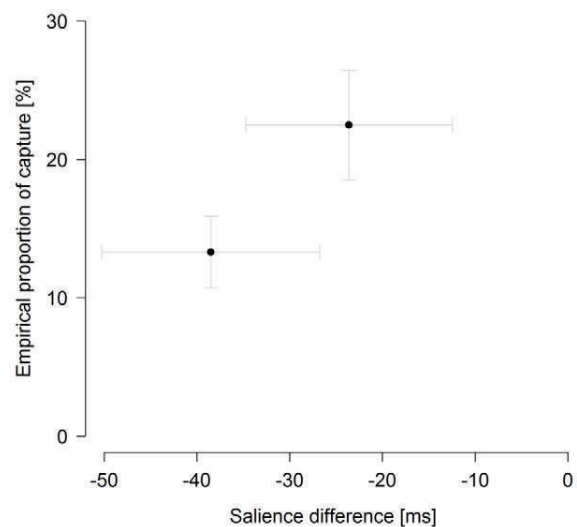


Figure 6. Capture of the eye by less salient distractors. Empirical proportion of capture by the distractor, averaged across participants, represents the proportion of first eye movements landing on the distractor position. Salience difference, averaged across participants, was derived from detection times in the baseline salience measurement requiring a simple target-present vs. target-absent decision (see *Methods of Behavioral eye-tracking experiment*). Negative x-values indicate distractors less salient than the target. Dots represent mean values of proportion of capture for each salience difference condition ($n = 2$); arrows indicate the associated standard errors. doi:10.1371/journal.pone.0052595.g006

events. This implies that distractors less salient than the target do give rise to involuntary attentional capture (as well as distractors more salient than the target).

The initial saccade latencies, irrespective of saccade destination, were examined in an ANOVA with the single factor distractor condition (three levels: absent, color distractor 1, color distractor 2). The latencies were somewhat shorter for distractor-absent trials ($M = 249$ ms, $SD = 20$) than for trials with a color distractor (distractor 1: $M = 256$ ms, $SD = 29$; distractor 2: $M = 256$ ms, $SD = 31$), but these differences were not reliable ($F[2,14] = 1.9$, $p = .19$). The same was true when only the latencies of initial target fixations were examined: latencies were slightly, but not significantly, shorter for distractor-absent trials ($M = 249$ ms, $SD = 20$) than for trials with a color distractor (distractor 1: $M = 259$ ms, $SD = 31$; distractor 2: $M = 256$ ms, $SD = 34$; $F[1,9] = 2.4$, $p = .16$, Greenhouse-Geisser-corrected).

Finally, we examined how long the eyes rested on the distractor when it was selected prior to the target. The mean fixation duration was 131 ms for color distractor 1 and 154 ms for color distractor 2. The 95% confidence intervals ranged from 95–160 ms for color distractor 1 and from 95–214 ms for color distractor 2. This means that the time required to identify the foveated item as a non-target and to prepare the next saccade varied between 95–214 ms.

This time can be related to the maximum RT interference in the behavioral distractor experiment. There, the asymptote of the sigmoidal relationship between salience difference and RT interference was about 80 ms. That is, distractors much more salient than the target, which are presumably selected first in 100% of all trials, lead to RT interference of approximately 80 ms. This time is in a similar range (albeit somewhat faster) to the durations of first fixations on distractors. Note, though, that the focus of the present study and model is on the capture of attention,

rather than the subsequent processing steps which include identification of the selected item as a distractor, selection of the next salient location, disengagement of attention, and execution of the covert or overt attention shift. These processing stages subsequent to attentional capture have only rarely been discussed in the literature [3] and should be the subject of future research. The two methods presented here (fixation durations and maximum RT interference) may serve as two possibilities of how to estimate the duration of the subsequent processing stages.

General Discussion

Theories of attentional selection, such as salience and visual search theories [10,18–21], assume attention to be automatically attracted by the most salient location. An additional assumption of these theories is noise operating during the computation process. This assumption of noise requires the distinction between stimulus salience, determined by physical stimulus properties, and the salience estimate for selection which is susceptible to noise – selection salience. Although there are empirical studies providing evidence for attentional capture by the most salient stimulus [11,12,14], there has been no previous study in which salience of a target and salience of a distractor were varied parametrically, to demonstrate that noise influences the process of selection between two competing locations and turns salience into a stochastic variable such that even less salient stimuli lead to RT interference because they may be selected prior to the most salient ones. Note that the assumption of noise influencing the selection process is also at the heart of the redundant-signals paradigm. Here, two salient features share the same location while racing for selection [60,61].

The aim of the present study was to test the predictions by visual search and salience models that noise influences the selection process such that (i) selection salience (based on which a selection is made) varies as a function of relative salience between target and distractor and (ii) distractors less stimulus-salient than the target capture attention. Further, by implementing the distinction between stimulus and selection salience computationally, we aimed at modelling the empirical results of the distractor visual search experiment.

By manipulating stimulus salience of targets and distractors parametrically, we found distractor interference to be sigmoidally related to salience difference between targets and distractors and even distractors less salient than the target to interfere with search and capture attention. These results are in accordance with salience [18–20] and visual search models [8,10,21], which assume noise during the selection process. This, at the same time, suggests that experimental manipulations of previous studies [11,12,14,16] were insufficient to recognize the stochastic dependency between salience and attentional capture and hence claimed that the most (stimulus-) salient item is invariably selected first. Parametric salience manipulation, by contrast, revealed a gradual increase of RT interference with increasing distractor salience relative to the target, where a less salient distractor can be selected before the more salient target. These results point to a stochastic relationship between stimulus salience and selection, which is predicted by visual search and salience models, but was not shown in relevant empirical studies [11,12,14,16].

Attentional Selection as Decision Process

For the computational implementation of the distinction between stimulus and selection salience, we considered attentional selection as a decision between the target and the distractor (non-targets were considered negligible in the competition for selection,

because it was ensured that all target and all distractor stimuli were found efficiently, i.e. popped-out) and used decision mechanisms to model selection salience on the basis of stimulus salience. The idea to implement attentional selection as a decision process is grounded on the assumption that search does not involve a one-step decision [62–64], but rather a chain of decisions [10,65,66]. In this chain, first, one of n possible locations has to be selected (where n is the number of possible target locations in the display); second, a two-alternative identification decision between ‘target’ and ‘distractor’ has to be made; third, a decision concerning the response-relevant feature (here the gap location) is necessary for task completion; and fourth, the correct button has to be selected for the response (here upper or lower).

As input for the selection salience modelling, we used the stimulus salience estimates measured in the detection experiment. Selection salience was then computed by the race of the two accumulators of target and distractor with their drift rates corresponding to the stimulus salience of both stimuli. In other words, the model was first fit to the RT distributions in the salience baseline measurement, which was designed to provide estimates of the drift rate parameters corresponding to the stimulus salience values of the various (orientation and luminance) target stimuli. This procedure of taking empirical data as input for the model to simulate visual search performance was also used by Purcell et al. [35]. When, second, using these empirical stimulus salience parameters to simulate the data of the distractor experiment, the proportion of simulated capture (i.e. trials on which the distractor was selected first) did not differ from that of empirical RT interference and increased with increasing relative stimulus salience between target and distractor. The model also simulated capture by less salient distractors, as indicated in the RT distractor experiment and demonstrated in the eye-tracking experiment.

The present approach of considering salience-based attentional selection as decision process (with a decision being made in favor of the stimulus with the highest selection salience), is only one way to conceive of salience. An alternative approach is that adopted by image-based salience models [22–24], which implement the construct of salience in terms of image statistics that are computed by center-surround algorithms. In this case, however, the most salient item is invariably selected, unless some noise filter is added on top of the computed salience. For the computation process itself, stimulus salience and selection salience are always identical in these models, that is, noise is not an inherent component of the computation process, but a ‘technical’ add-on following the computation of salience. A more theoretical, rather than technical, approach was taken in developing cognitive concepts of salience to explain specific patterns in visual search performance [10,17,21]. Here, the core function of salience (or activation) maps is their role in guiding attention to a specific location. Another perspective that has been taken to consider salience is the neurophysiological one [19,67–70]. Here, the spike rates of neurons in the lateral intraparietal area or the frontal eye field are considered to form a salience map and marking locations for focal-attentional allocation. Some attempts have already been undertaken to combine the various constructs of salience: Li [20] presented a salience model based on neuronal network modelling of V1 that combines the cognitive, neurophysiological, and image statistics perspectives. Purcell et al. [35] combined the decision with the neurophysiological approach by feeding neuronal spike trains as salience signal to a stochastic accumulator model that simulated a decision in a visual search task. The variety of perspectives from which salience can be considered demonstrates that when various studies talk about salience, the authors do not necessarily have the same concept in mind. Thus, clearly, it is necessary to precisely define

the concept under consideration, in order to frame predictions about behavior.

Relation to Biased Competition

As mentioned above, RT interference due to distractor presence can have several possible sources. Either the distractor could capture attention and the target would be selected only as the second item, yielding a cost on RT; or the distractor could slow down selection of the target, even if the target is selected first. Here, we discuss these two theoretical possibilities with respect to the concept of biased competition [58,71,72]. The core assumption of biased competition is the idea that stimuli compete for neuronal representation. The competition for this representation can be biased by both top-down (intentional) and bottom-up (environmental) factors. The bottom-up factor relevant in this context is salience [73]: the more salient a stimulus is, the stronger it competes for neural representation. There are two possibilities of how this account can be linked to the distractor visual search paradigm.

First, biased competition could account for no-capture slowing of target selection. Target and the distractor compete for neural representation. Thus, when a distractor is present, fewer resources are available for the target. Even if the target is selected first, its selection time would be slower in the presence, compared to the absence, of a distractor. This could be implemented in our model in terms of lateral inhibition between the different accumulators [52,74]. That is, each accumulator receives excitatory input from the salience signal derived from its stimulus and, additionally, inhibitory input from the other accumulators. However, while such a wiring scheme would implement the biased-competition mechanism sketched above, our eye movement experiment yielded little indication that the time required for direct (first) selection of the target is dependent on distractor presence (or distractor salience).

Second, our decision model – which assumes an accumulator for each stimulus in the visual field, with the drift rate of each being proportional to the stimulus salience – can be considered as an implementation of the bias in competition imposed by stimulus salience [73]. In the model, competition takes the form of a race, amongst the accumulators, against a threshold: that item is attentionally selected that drives the accumulator which crosses the threshold first, where the driving input depends on stimulus salience.

In summary, both variants of biased competition (yielding target slowing and distractor capture, respectively) can be implemented in our salience decision model. However, our eye movement data suggest that primarily the latter mechanism is responsible for the RT interference caused by a competing distractor, whether the distractor is more or less salient than the target.

Relation to Top-down Modulations of Salience

The focus of the present study was on bottom-up modulations of salience by physical feature contrast. Top-down modulations of

salience are well documented in the literature [10,48,50] and have also been discussed in relation to attentional capture [49,75,76]. Specifically, it is assumed that when a dimension (e.g. orientation) is task-relevant, salience signals from this dimension are up-modulated to some degree. At the same time, salience signals from irrelevant or to-be-ignored dimensions (e.g. luminance or color) are down-modulated. Our data support this view, in that the salience difference at which the target and the distractor are equally likely to be selected actually requires the distractor to be somewhat more salient than the target, as measured in the baseline experiment (because in the distraction experiment, top-down weights enhance the target and reduce the distractor salience). The present model can easily be extended to incorporate top-down weighting: the drift rates would be slightly increased for features in the target-defining dimension and decreased for features in the distractor-defining dimension, implementing task-dependent top-down modulations of salience.

Conclusion

We conclude that attentional selection can be understood as a ‘decision’ and, consequently, with regard to the concept of salience, a distinction has to be made between *stimulus salience*, which is computed from physical stimulus properties, and *selection salience*, which contains the noisy estimate of stimulus salience that is relevant for attentional selection. Following this distinction, the dependency between attentional selection and salience is stochastic in nature. As an empirical consequence, attentional capture by an irrelevant distractor occurs as long as the selection time distributions of target and distractor overlap, and distractors less salient than the target can also capture attention.

Supporting Information

Text S1 Pilot Experiment.
(DOCX)

Table S1 Slopes and intercepts of the search RT functions for orientation and luminance contrast conditions.
(DOCX)

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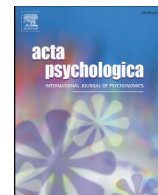
Author Contributions

Conceived and designed the experiments: MZ AIK HG HJM. Performed the experiments: AIK HG. Analyzed the data: AIK MZ HG. Wrote the paper: MZ AIK HG HJM. Performed computational modelling: MZ.

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Distractors less salient than targets capture attention rather than producing non-spatial filtering costs



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Non-spatial filtering

ABSTRACT

Distractors that are less salient than the target evoke reaction time interference in the distractor search paradigm. Here, we investigated whether this interference indeed results from spatial attentional capture or merely from non-spatial filtering costs. Target and distractor salience was manipulated parametrically and the modulation of reaction time interference by the distance between both stimuli was taken as an indicator of attentional capture. For distractors that were less salient than the target, we found distance to be predictive of reaction time interference. Moreover, this relationship was modulated by the difference in relative salience of target and distractor: the less salient the distractor was compared to the target, the weaker was the influence of distance. These results are in accordance with the sequential sampling model of salience-based selection by Zehetleitner et al. (Zehetleitner, M., Koch, A.I., Goschy, H., Müller, H.J., 2013. Salience-based selection: Interference by distractors less salient than the target. *PLoS ONE* 8: e52595.). This model assumes the salience map to be computed by noisy accumulation of sensory evidence. As a result, the salience map output fluctuates around its true value and less salient locations can be denoted as most salient. A distractor less salient than the target can therefore capture attention with a certain probability. We conclude that reaction time interference by less salient distractors in the distractor search paradigm is a result of attentional capture in a proportion of trials, rather than a result of non-spatial filtering costs.

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1. Introduction

Every instant of time, numerous signals reach the sensory system – more than the brain can efficiently process up to the level of conscious awareness and decision making. Given this, selective attention is required to focus processing on ‘relevant’ objects or locations. This focusing can happen in an agent-based or top-down acting manner as well as in an environment-based or bottom-up acting fashion (Egeth & Yantis, 1997). Accordingly, attention can be allocated intentionally to a stimulus, based on parameters (e.g. spatial location, features, dimensions, objects) specified in the ‘attentional set’ (Folk, Remington, & Johnston, 1992); alternatively, attention can be reflexively summoned by a salient stimulus (Theeuwes, 1992).

Stimulus salience refers to the conspicuity, or contrast, of an item relative to its surrounding items: the more homogeneous the background of a given item is and the more it differs from the background, the more salient it is (Duncan & Humphreys, 1989; Itti & Koch, 2001; Koch & Ullman, 1985; Wolfe, Cave, & Franzel, 1989). With regard to

the influence of salience on attentional capture, the debate has mostly been centered on whether or not the most salient, but task-irrelevant, non-target item invariably captures attention, whereas the influence of items less salient than the target has largely been neglected. On influential salience models (Bruce & Tsotsos, 2009; Itti & Koch, 2001), one would predict the most salient item to capture attention invariably – which is well supported by behavioral (Donk & Van Zoest, 2008; Kim & Cave, 1999; Mounts, 2000; Theeuwes, 1991, 1992) and physiological evidence (De Fockert, Rees, Frith, & Lavie, 2004; Hickey, McDonald, & Theeuwes, 2006; Hodsoll, Mevorach, & Humphreys, 2009). For instance, in the classical distractor search paradigm, Theeuwes (1991, 1992) presented a salient target among homogeneous non-targets and one salient (non-target) distractor. He found singleton distractors more salient than the target to interfere with search (i.e., to slow reaction times to the target), whereas interference was not evident with targets more salient than the distractors. Because distractor interference was observed, in the former case, even though participants knew the exact target-defining feature, Theeuwes concluded that salience was the critical factor determining priority of, or first, attentional selection. Although Theeuwes’ (1991, 1992) strong ‘bottom-up’ stance has been challenged by findings that attentional capture can be top-down modulated by observers’ intentions (e.g. Bacon & Egeth, 1994; Eimer & Kiss, 2008; Leber & Egeth,

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2006; Müller et al., 2009; Zehetleitner, Goschy, & Müller, 2012), all accounts agree that if a distractor does capture attention, it must have been more salient – that is, it cannot have been less salient – than the target item (De Fockert et al., 2004; Theeuwes, 1992, 2010).

Given this ubiquitous assumption, it is unsurprising that little effort has been directed to systematically investigate interference by distractors that are less¹ salient than the target, probably because influential theories of salience-based selection predict no interference for this case (Theeuwes, 2010). To our knowledge, the first systematic study of this issue is that of Zehetleitner, Koch, Goschy, and Müller (2013), which yielded evidence of interference caused by less salient distractors. In more detail, varying target and distractor salience parametrically in a distractor search paradigm, Zehetleitner et al. (2013) found reaction time (RT) interference to correlate strongly with the relative salience between both items. Importantly, even distractors less salient than the target evoked RT interference – suggestive of attentional capture (Theeuwes, 1992). However, the finding that a distractor slows RTs to the target is per se not sufficient to infer that attention was actually captured by, that is, first directed to the distractor and only afterwards reoriented to the target. Rather, RT slowing could also result from non-spatial ‘filtering costs’ associated with resolving the competition between simultaneously presented, more or less salient stimuli (Folk & Remington, 1998, 2006; Kahneman, Treisman, & Burkell, 1983).

Given this, the dependency of performance on the distance between target and distractor has become a more accepted behavioral marker of spatial-attentional capture (as opposed to mere non-spatial filtering costs): performance deteriorates the closer the distractor is located to the target (Caputo & Guerra, 1998; Eriksen & St. James, 1986; Hickey & Theeuwes, 2011; Mounts, 2000, 2005; Mounts & Gavett, 2004; Theeuwes, Kramer, & Kingstone, 2004; Zehetleitner, Müller, & Proulx, 2009). This distance effect has been explained in terms of a ring of suppression around the attended location, making it hard to detect and respond to another item that falls within the suppressed region. For the distractor search paradigm, this means that after being allocated to the distractor, attention forms a ring of inhibition around its location; if the target is located at a position within this ring, selection takes longer compared to when it is located outside, that is, further away from the distractor (see Fig. 1). In the literature, this effect has been referred to as ‘Localized Attentional Interference (LAI)’ (Mounts, 2000, 2005; Mounts & Gavett, 2004). This LAI effect is considered to be a more precise indicator of attentional capture and has thus been used recently to infer capture in the distractor search paradigm (Hickey & Theeuwes, 2011; Turatto, Galfano, Gardini, & Mascetti, 2004).

However, studies designed to resolve the issue of capture versus non-spatial filtering costs by using the distance effect as a marker of capture, and its absence as indication of non-spatial filtering costs, have yielded rather inconsistent results. Zehetleitner et al. (2009) found a distance effect when target and distractor dimensions remained the same during experimental blocks and distractor presence was 50%. For conditions in which target and distractor never appeared at the same location, Becker (2007) reported a distance effect when the colors of the non-targets and the distractor swapped unpredictably across trials, but not when they stayed constant. However, for conditions in which target and distractor could share location on some trials, Becker (2007) found no distance effect when the colors of the target and non-targets swapped, but they did find an effect when the colors remained constant within blocks. Turatto and Galfano (2001), by contrast, obtained a distance effect, indicative of attentional capture, when target and distractor could share location and the colors of non-targets

¹ For reason of clarity, henceforth, the short-hand expression ‘less salient distractor(s)’ always implies the comparison with the target.

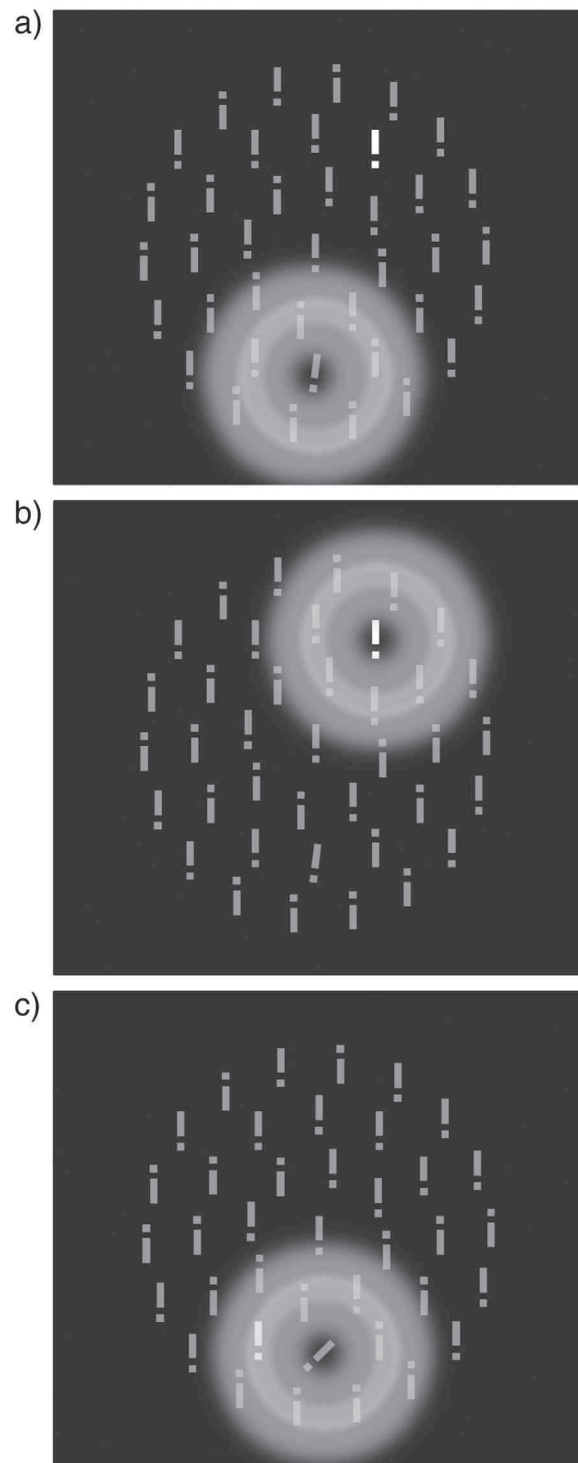


Fig. 1. Localized attentional interference effect. The closer the target (orientation-defined in the examples) is to the attention-capturing distractor (luminance-defined in the examples), the more it is suppressed. a) No capture by the distractor. Attention is allocated to, and the ring of suppression centered on, the target; the distractor does not influence performance. b) Capture by a distant distractor; the target is outside the suppressed area and therefore relatively easy to detect. c) Capture by a close distractor. The target is located in the suppressed region and therefore difficult to detect.

and distractor swapped unpredictably across trials. On the other hand, Hickey and Theeuwes (2011) found a distance effect both when target and distractor swapped colors across trials and when their colors stayed constant throughout a trial block – in a paradigm in which target and

distractor could never share location. When analyzing color repetition and swap trials separately in the mixed-block condition, capture was still found for the swap as well for the repetition trials. The only condition that yielded no indication of capture was that in which the target was more salient than the distractor. They took this as support for the notion that salience is decisive for attentional capture.

A somewhat different paradigm for examining whether target selection is slowed by capture or non-spatial filtering costs was used by Folk and Remington (1998). A cue display that preceded the search (i.e., target) display could contain a color singleton distractor, formed by four small circles surrounding the position markers where the target display stimuli would be presented later. The color target, predefined by its hue, could subsequently be presented at either the same or a different location than the distractor. The target was a color singleton in half the trials and a non-singleton (in which case another colored non-target singleton of a different hue was presented) in the other half of the trials. While the target color was kept constant throughout the experiment, distractor conditions were varied block-wise: 'same color as target', 'different color to target', and, respectively, 'no distractor'. The task was to indicate the targets' form identity (i.e., whether it was a '+' or an '=' sign) by a speeded two-alternative choice. Folk and Remington (1998) obtained a distance effect only when the distractor had the same color as the target, whereas a distractor of a different color was found to produce distance-independent costs when compared with the 'no distractor' condition. Folk and Remington (1998) concluded that distractors of the same color capture attention, whereas distractors of a different color induce non-spatial filtering costs. Whether or not it is possible to find a coherent account for all these disparate results, common to all these studies is that they posed the question of capture versus non-spatial filtering only for more salient distractors; none has considered this issue with regard to distractors less salient than the target.

The present study was designed to investigate whether the RT interference caused by less salient distractors is indeed attributable to attentional capture, as proposed by Zehetleitner et al. (2013), or rather to non-spatial filtering costs. Note that the arguments advanced by Zehetleitner et al. (2013) in favor of capture were mainly *theoretical*: they were based on the modeling of the observed RT interference effects by means of a probabilistically operating capture mechanism, which described the empirical data remarkably well. Going beyond this approach, the present study was intended to provide *empirical evidence* of attentional capture by examining for the presence versus absence of a distance effect as markers for capture and non-spatial filtering costs, respectively. In more detail, in both experiments of the study, we applied parametrical target–distractor relative salience and distance manipulations in a distractor search paradigm and examined whether distance has an effect on RT interference for varying salience differences between the target and the distractor. To assess the generality of any distance effects revealed, the two experiments introduced different distractor dimensions: in Experiment 1, which was essentially a re-analysis of Zehetleitner et al. (2013), participants searched for an orientation-defined target and ignored a (relative to the target) brighter distractor; in Experiment 2, they had to ignore a (relative to the target) differently colored distractor. If less salient distractors, independently of their defining dimension, do indeed capture attention, distance would be expected to have an influence on RT interference; by contrast, no distance effect would be expected if less salient distractors cause merely non-spatial filtering costs (without actually summoning attention to their location). Moreover, if different proportions of capture events (i.e., trials on which capture occurs) account for the increase in RT interference with relative salience, as hypothesized by Zehetleitner et al. (2013), one would also expect a modulation of the correlation between salience and RT interference by target–distractor distance.

2. Experiment 1

2.1. Methods

The methods were as in Zehetleitner et al. (2013).

2.1.1. Participants

Eighteen participants took part for course credit or € 16. The data of one participant had to be discarded because of technical problems. The remaining 17 had a median age of 26 (range 20–50) years; five were male, all were dextral, and all had (corrected-to-) normal visual acuity.

2.1.2. Stimulus presentation and data acquisition

The experiment was conducted in a sound-insulated booth, and was controlled by a program purpose-written in C++. Stimuli were presented on a 19" View Sonic Graphics Series G 90 fB monitor at a resolution of 1024 × 768 pixels and a refresh rate of 85 Hz; viewing distance was approximately 57 cm. Participants responded using their left and right index fingers, respectively, to press the upper or lower button of a purpose-built response pad. RTs and response accuracy were recorded online.

The display consisted of 39 vertical broken gray bars presented on black background and arranged equidistantly on three imaginary concentric circles (1.9°, 3.3°, and 4.6° of visual angle in radius, with 8, 12, and 18 bars, respectively) around the center of the screen. The bars were 1.13° × 0.25° in size and had a 0.13°-gap randomly located at the top or bottom of each bar. Targets differed from non-targets in orientation (7, 8, 9, 14 and 45° tilted from vertical), and distractors differed from non-targets in luminance (13.8, 14.8, 17.9, 19.4, and 25.5 cd/m²). Distance between target and distractor could be 0, 1, 2, 3, 4, or 5 stimuli in between. A pilot experiment was conducted to ensure that target and distractor salience was sufficient for these stimuli to 'pop out' from the search array, i.e., their associated detection times were independent of the number of non-targets in the display.

2.1.3. Design and procedure

Two 1-h sessions were carried out on consecutive days, at the same time of day. The first part of each session was the distractor experiment; the second part was a post-experiment for stimulus salience measurement (for the latter, see Section 2.1.4). For the distractor experiment, factors manipulated within participants were distractor presence (present vs. absent), target salience (five levels), and in case of distractor presence, distractor salience (five levels) and target–distractor distance (six distances). A target was present on all trials; distractors occurred randomly in 50% of the trials. Each target and distractor salience combination occurred equally often. A target and a distractor (when present) could appear only at one of the 12 positions of the second (intermediate) circle of the stimulus display, to keep the distance of the target and, respectively, distractor from the display center constant; their exact positions – and, as a result, the distance between them – was chosen randomly, with the constraint that the target and distractor could never share the same location. Importantly, relative target–distractor salience and distance was randomized within trial blocks. Participants completed 20 blocks of 50 trials each day, yielding a total of 2000 trials.

Each trial started with a white fixation dot, presented for a duration uniformly distributed between 900 and 200 ms, that was superseded by the search display which remained present until response (Fig. 2a). Participants were instructed to indicate, as quickly and accurately as possible, the gap location (top or bottom) of the target by pressing the upper or lower button, respectively. In case of an error, visual feedback was provided, followed by an additional 500-ms blank screen before the next trial. At the end of each block, participants were informed about their mean RT and error rate.

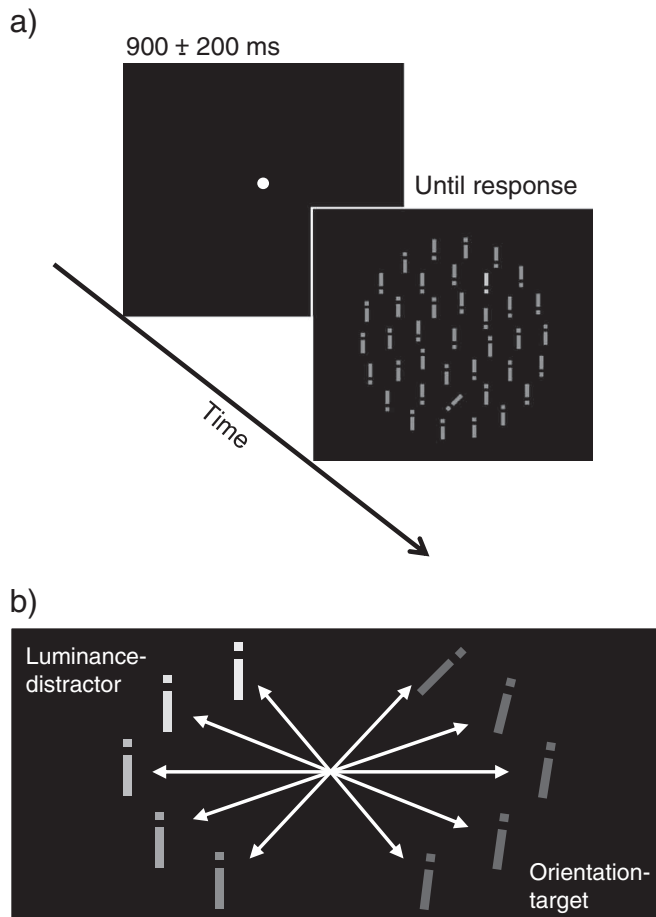


Fig. 2. Procedure and stimuli in Experiment 1. a) Trial sequence. The oriented bar served as target, whereas the bright bar was the to-be-ignored distractor. b) 25 salience conditions in the distractor search paradigm (target orientation: 7, 8, 9, 14, 45° × distractor luminance: 13.8, 14.8, 17.9, 19.4, and 25.5 cd/m²). Note that the salience values in the illustration are not veridical.

2.1.4. Stimulus salience measurement

Because salience is a psychological construct, rather than a physical given, we used a behavioral measurement of salience, which was collected in a post-experiment after each session of the distractor experiment. Stimuli were the same as in the distractor experiment. All target orientation and distractor luminance contrasts from the distractor experiment (Fig. 2b) were presented as (to-be-detected) targets randomly intermixed with target-absent displays (as in the distractor experiment, targets never occurred on the outer circle). The design was 2 (target presence vs. absence) × 2 (dimension luminance vs. orientation) × 5 (contrast) factorial. Participants' task was to indicate the presence of an orientation or luminance target via button press; response was to be withheld if no target was present. Four blocks consisting of 80 trials were performed each day, yielding a total of 640 trials and 32 trials per contrast condition. The stimulus display was presented until response or a maximum duration of 1200 ms.

Using these detection RTs as our measure of stimulus salience, we calculated the relative salience between stimuli by subtracting distractor salience from target salience, separately for each participant and relative salience condition. For example, if a target was detected at a rate of 350 ms and a distractor at one of 400 ms, then their salience difference was considered to be -50 ms. Note that items of higher salience are associated with shorter RTs; negative values of relative salience indicate a distractor less salient, and positive values a distractor more salient than the target. This relative salience measure, served as independent variable in the main distractor experiment.

2.1.5. Data analysis

Only correct-response trials were used for analysis (distractor experiment: 96.1%; stimulus salience measurement: 98.6%), excluding RTs shorter than 150 and longer than 1500 ms in the distractor experiment (1.3%) and shorter than 150 and longer than 1000 ms in the stimulus salience measurement (0.3%). The first 20 trials (the first 10 trials of the stimulus salience measurement) of each session and the first 3 trials of each block served as practice trials and were also excluded from analysis.

We employed hierarchical linear modeling to examine whether distance has an impact on RT interference when distractors are less salient, as well as more salient, than the target. The modeling was applied separately to the data subset with less salient distractors, as well as to the subset with more salient distractors, and the whole data set (including both less and more salient distractors). The method of hierarchical linear modeling takes care of repeated measures in regression analysis by taking into account different levels in the data structure. As the same participant performs many trials of the same experimental condition in typical cognition research, the data structure is nested, with single-trial RTs (observation level 1) being dependent on the higher, individual-participant level (group level 2). To take this nested data structure into account, single-trial RTs were aggregated only across trials of the same condition and participant, rather than across participants. RT interference was then calculated by subtracting RTs of target-only trials from RTs of target-plus-distractor trials. This was done separately for each participant and relative salience × target–distractor distance condition. Relative salience was calculated by subtracting distractor salience from target salience (see Section 2.1.4).

For our hierarchical linear models, we factored in distance, relative salience, and their interaction as fixed effects on RT interference, and participant as random intercept effect. Stepwise selection of predictors was applied in the following sequence: no predictor (model 1), distance (model 2), distance + relative salience (model 3), and distance + relative salience + distance × relative salience (model 4). The hierarchical linear model equation was: $y_{ij} = \beta_{0j} + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{1i} x_{2i} + \varepsilon_{ij}$ with $\beta_{0j} = \gamma + u_j$. For level 1, y_{ij} is the interference on trial i for participant j , β_{0j} is the participant-specific intercept, β_1 is the fixed effect of distance on trial i , $\beta_2 x_{2i}$ is the fixed effect of relative salience on trial i , $\beta_3 x_{1i} x_{2i}$ is the fixed effect of the interaction distance × relative salience on trial i , and ε_{ij} is the residual. For level 2, that is, the intercept of each participant, γ is the mean (i.e., fixed-effect) intercept and u_j the participant-specific deviation of the mean.² To test for significance of each predictor, we compared the next more complex model's goodness-of-fit to that of the previous, more parsimonious one, using χ^2 -tests and the Bayes Information Criterion (BIC; Schwarz, 1978). Following Whisman and McClelland (2005), for the analyses of the two data subsets (with less and, respectively, more salient distractors), predictors were centered (i.e., the mean of the variable was subtracted from each value, so as to yield a mean of 0) because the values of 0 ms relative salience (equal salience of distractor and target) and of 0 units of distance between target and distractor (target and distractor at same location) were outside the examined range. For the same reason, in the analysis for the whole data set, distance was centered, while relative salience was not – the latter because the 0 ms value corresponds to the target and distractor being equally salient, so that the regression coefficient can be meaningfully interpreted without centering. For centered predictors, regression coefficients represent the main effects also in models including interaction terms.

To examine the interaction or moderator effect more closely, that is, to test whether the influence of distance varies as a function of relative salience, we calculated the simple relationships between interference and distance at different values of relative salience (Bauer &

² Note that in the literature, there are different usages of the notations in these equations; we follow that of Bauer and Curran (2005).

Curran, 2005). This is expressed by re-arranging the equations of the hierarchical linear model to $\mu_{y|x_2} = (\gamma + \beta_2 x_2) + (\beta_1 + \beta_3 x_2) x_1$, where $\mu_{y|x_2}$ is the predicted mean interference as a function of distance conditional on the relative salience value. The first term of the sum in the equation represents the simple intercept and the second term the simple slope, both dependent on the value of relative salience. We calculated the simple slopes for three different values of relative salience, namely, the 25%, 50%, and 75% quartiles of the respective distribution of relative salience values. Quartiles for the respective data sample (less salient, more salient, or whole data set) were estimated using the default procedure of R (R Development Core Team, 2010). Significance of simple slopes and the significance boundary (i.e., the value of relative salience below which slopes are no longer significant) were calculated using the online tool provided by Preacher, Curran, and Bauer (2006).

Statistical tests were conducted on $N = 8848$ level-1 observations (relative salience \times distance) for the data subset with less salient distractors, $N = 5974$ level-1 observations for the subset with more salient distractors, and on $N = 14,822$ level-1 observations for the whole data set. For all data sets, statistical tests were conducted on $N = 17$ level-2 groups (participants); the significance level adopted was .05. Hierarchical linear modeling was carried out using the lme4 package (Bates & Maelcher, 2010) of R (R Development Core Team, 2010).

2.2. Results and discussion

For less salient distractors, the mean RT was 630 ms ($sd = 103$ ms) and the mean interference 13 ms ($sd = 71$ ms). Table 1 presents estimates of the fixed and random effects and Table 2 depicts the results of the model comparisons along with the significance of each predictor. As can be seen from Table 1, RT interference was the greater the smaller the distance between target and distractor (witness the negative coefficient). This effect of distance is significant, as model 2, with the single predictor distance, provides a significantly better fit than model 1, without any predictors (see Table 2). This is consistent with the assumption that less salient distractors do capture attention. Additionally, relative salience is a significant predictor of RT interference: interference increases with increasing salience of the

Table 2
Hierarchical linear model comparison for Experiment 1.

Model	χ^2	BIC
<i>Less salient distractors</i>		
1		112,607
2	60.43**	112,556
3	28.58**	112,536
4	14.81**	112,531
<i>More salient distractors</i>		
1		79,273
2	105.46**	79,177
3	29.00**	79,156
4	4.79*	79,160
<i>Whole data set</i>		
1		192,582
2	159.12**	192,432
3	244.53**	192,159
4	44.24**	192,163

Note. BIC: Bayes Information Criterion.

* $p < .05$.

** $p < .01$.

distractor relative to the target. This effect is evidenced by model 3, which includes relative salience as additional fixed effect, fitting significantly better than model 2. Finally, the effect of distance on RT interference varies dependent on relative salience. This moderating effect is also significant, as model 4, which includes the interaction of distance and relative salience as predictor, fits significantly better than model 3 (without the interaction term). In summary, the moderator model (model 4) fits the data best overall when taking into account both significance tests and BIC scores.

To examine the dependency of RT interference on target–distractor distance for different values of relative salience, as indicated by the significant interaction, we calculated simple intercepts and simple slopes, that is, we regressed RT interference on distance conditional on specific values of relative salience. The three relative salience values chosen were the 25%, 50%, and 75% quartiles of the data subset with less salient distractors. A significant interaction term implies that simple slopes differ dependently on the value of relative salience, but

Table 1

Fixed effects and variance estimates for the relationship between distance, relative salience, and RT interference in Experiment 1.

	Model 1	Model 2	Model 3	Model 4
<i>Less salient distractors</i>				
Fixed effects				
Intercept	13.57 (2.21)	13.57 (2.19)	13.44 (2.37)	13.39 (2.39)
Distance		−7.14 (0.92)	−7.09 (0.92)	−7.13 (0.91)
Relative salience			0.22 (0.04)	0.23 (0.04)
Distance \times Relative salience				−0.09 (0.02)
Random effect				
Participant	43.17 (6.57)	42.48 (6.52)	55.95 (7.48)	58.03 (7.62)
<i>More salient distractors</i>				
Fixed effects				
Intercept	52.69 (4.71)	52.59 (4.60)	53.99 (4.65)	54.03 (4.60)
Distance		−15.21 (1.47)	−15.32 (1.47)	−15.31 (1.47)
Relative salience			0.42 (0.08)	0.42 (0.08)
Distance \times Relative salience				−0.10 (0.05)
Random effect				
Participant	266.78 (16.33)	250.15 (15.81)	257.21 (16.04)	249.58 (15.80)
<i>Whole data set</i>				
Fixed effects				
Intercept	29.15 (3.38)	29.14 (3.33)	35.04 (3.13)	35.13 (3.11)
Distance		−10.28 (0.81)	−10.34 (0.81)	−11.85 (0.84)
Relative salience			0.37 (0.02)	0.38 (0.02)
Distance \times Relative salience				−0.09 (0.01)
Random effect				
Participant	164.84 (12.84)	159.64 (12.64)	135.36 (11.63)	133.40 (11.55)

Note. Predictors were centered as stated in the analysis section. Coefficients (standard errors) are reported for fixed effects and variance estimates (standard deviations) are presented for random effects.

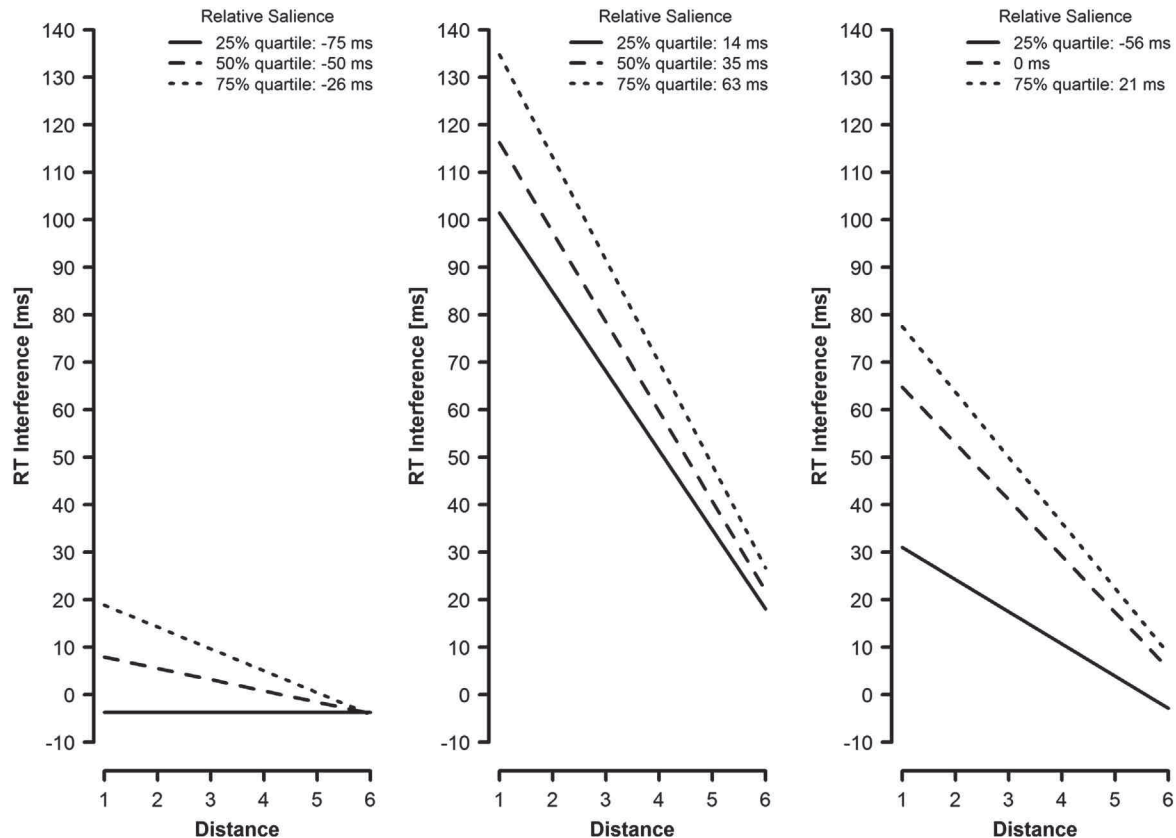


Fig. 3. Interaction effects in Experiment 1. RT interference as a function of target-to-distractor distance (i.e., the number of non-targets between target and distractor), conditional on relative salience (distractor minus target). Simple slopes are depicted for different relative salience values. Left panel: data subset for less salient distractors. Middle panel: data subset for more salient distractors. Right panel: whole data set.

whether each slope actually differs from zero, that is, whether a correlation exists, needs to be tested additionally. The left panel of Fig. 3 presents the simple slopes for the 25% (−75 ms relative salience), 50% (−50 ms relative salience), and 75% (−26 ms relative salience) quartiles of (negative) relative salience values in terms of the respective (target minus distractor) detection time differences. While the slopes for the 25% and 50% quartiles were non-significant (−75 ms: 0.01, $z = 0.00$, $p = .996$; −50 ms: −2.37, $z = -1.55$, $p = .121$), that for the 75% quartile was significant (−26 ms: −4.61, $z = -4.13$, $p < .001$). As can be seen from the left panel of Fig. 3, interference decreases with increasing distance, but to a different degree dependent on the relative salience between target and distractor: when the distractor is only a little less salient than the target, as for the 75% quartile, the influence of distance on interference is strong, but the effect weakens or vanishes as the salience of the distractor decreases relative to that of the target (at the 50% and 25% quartiles). The significance boundary for the simple slopes was −45 ms relative salience; that is, for relative salience values smaller than −45 ms, simple slopes were no longer significantly different from zero. Restated: distractors can be up to 45 ms less salient than the target and still capture attention.

To corroborate that the same pattern is also evident with distractors more salient than the target, as has been reported many times in the literature, we conducted the same analysis for the data subset with more salient distractors. For this subset, the mean RT was 739 ms ($sd = 135$ ms) and the mean interference 56 ms ($sd = 107$ ms). For more salient distractors, too, hierarchical linear modeling revealed smaller distances to yield greater RT interference (Table 1), as indicated by the significantly better fit of model 2 over model 1 (Table 2). Furthermore, the influence of relative salience on RT interference was also significant, as model 3 outperformed model 2. Finally, the interaction between the two turned out to be significant

too, as model 4 fit the data significantly better than model 3. However, although the significance tests favor model 4 overall, the BIC statistics prefer model 3. The latter are indicative of the interaction term contributing little to the predicted RT interference. Thus, compared to the distractors less salient than the target (see above), the contribution of the interaction term is less reliable for more salient distractors.

Since the significance tests revealed a significant interaction, we conducted the interaction analysis also for the data subset with more salient distractors; see the middle panel of Fig. 3 for the results. The simple slopes for the 25% quartile (14 ms relative salience), 50% quartile (35 ms relative salience), and 75% quartile (63 ms relative salience) were all significant (14 ms: −16.66, $z = -10.46$, $p < .001$; 35 ms: −18.87, $z = -8.63$, $p < .001$; 63 ms: −21.62, $z = -6.69$, $p < .001$). That is, the effect of distance on RT interference, although manifest for all distractors more salient than the target, decreased to a differential degree depending on the relative salience between target and distractor.

Finally, to cover the whole range of examined relative salience values (making the results comparable to those of Zehetleitner et al., 2013), the hierarchical linear models were also calculated for the whole data set. The overall mean RT was 670 ms ($sd = 127$ ms) and the mean interference 28 ms ($sd = 88$ ms). In this analysis, too, distance and relative salience significantly predicted RT interference (see Tables 1 and 2). In addition, the interaction term in model 4 was significant, as this model fit the data significantly better than model 3. However, as with the more salient distractors, the BIC statistics favored model 3 over model 4.

To examine the moderating effect by relative salience more closely, simple slopes and intercepts were calculated for the 25% and 75% quartiles as well as the relative salience value of 0 ms (we chose 0 ms instead of the 50% quartile because this point denotes equal target and distractor salience). The right panel of Fig. 3 presents the

simple slopes for the 25% quartile (-56 ms relative salience), 0 ms relative salience, and the 75% quartile (21 ms relative salience). All three simple slopes were significant (-56 ms: -6.78 , $z = -7.02$, $p < .001$; 0 ms: -11.85 , $z = -14.17$, $p < .001$; 21 ms: -13.77 , $z = -14.41$, $p < .001$). The figure shows that for the whole data set, too, interference decreases with increasing distance, but again to a different degree dependent on the relative salience between target and distractor: the more salient the distractor is compared to the target, the stronger the influence of distance on RT interference.

Taken together, the results of Experiment 1 revealed distance to modulate RT interference – a clear indication of attentional capture by the distractor. While this would be expected on most existing theories of attentional capture for more salient distractors, it is also true for distractors less salient than the target. This confirms our hypothesis that the latter do indeed capture attention, rather than interference being merely a product of non-spatial filtering processes. The finding that relative salience is a significant predictor was already reported in Zehetleitner et al. (2013). Going beyond this, the present analyses revealed an influence of distance modulated by the relative salience of target and distractor: the influence of distance was the greater the more salient the distractor was compared to the target. This can be explained by differential proportions of (discrete) capture and non-capture events, with the proportions being dependent on relative salience. We consider this notion of proportional capture in more detail in Section 4.

3. Experiment 2

3.1. Methods

The methods of Experiment 2 were the same as of Experiment 1, unless expressly stated otherwise.

3.1.1. Participants

Eighteen participants took part in Experiment 2; one of them had to be excluded due to technical problems. Four of the remaining 17 participants had already taken part in Experiment 1. Median age was 26 (range 20–49) years; four were male; and 14 were dextral.

3.1.2. Stimulus presentation and data acquisition

Stimuli were presented on a 20" Mitsubishi Diamond Pro 2070^{SB} monitor at a resolution of 1280×1024 pixels and a refresh rate of 100 Hz; viewing distance was approximately 73 cm. Participants responded using their left and right index fingers, respectively, to press buttons 2 and 8 of the numeric keypad of an Empirisoft DirectN keyboard. RTs and response accuracy were recorded online. Radii of stimuli circles were 1.18° , 2.2° , and 3.06° of visual angle, respectively, and bar size was $0.71^\circ \times 0.16^\circ$ with a 0.08° gap. Target orientation was a tilt of 9, 10, 11, 16, and, respectively, 45° from the vertical, and distractor colors were different shades of red (RGB 173/107/114, 181/103/110, 185/97/104, 210/78/87, 252/0/21), with constant luminance of all presented stimuli (16.2 – 17.3 cd/m²).

3.1.3. Design and procedure

The design and procedure were the same as in Experiment 1 (Fig. 2a).

3.1.4. Baseline salience measurement

This was analogous to Experiment 1, but with the targets being color and orientation defined (rather than luminance and orientation defined, as in Experiment 1; Fig. 2b).

3.1.5. Data analysis

Only correct-response trials were used for analysis (distractor experiment: 96.4%; baseline salience measurement: 99.2%), excluding RTs shorter than 150 and longer than 1500 ms in the distractor

experiment (1.4%) and shorter than 150 and longer than 1000 ms in the Section 3.1.4 (0.2%). Hierarchical linear modeling analyses were analogous to those in Experiment 1. Tests were conducted on $N = 6025$ level-1 observations (relative salience \times distance) for the data subset with less salient distractors, $N = 8813$ level-1 observations for the data subset with more salient distractors, and on $N = 14,838$ level-1 observations for the whole data set. For all data sets, statistical tests were conducted on $N = 17$ level-2 groups (participants).

3.2. Results and discussion

For less salient (color-defined) distractors, the mean RT was 643 ms ($sd = 98$ ms) and the mean interference 8 ms ($sd = 71$). Model estimates are presented in Table 3 and model comparisons are summarized in Table 4. For less salient, color-defined distractors, too (as well as for the less salient luminance-defined distractors in Experiment 1), RT interference increased with decreasing distance. This distance effect was significant, as model 2 fit the data better than model 1. That is, less salient distractors defined in the color dimension do also capture attention (as well as the luminance-defined distractors in Experiment 1). The contribution of relative salience to the prediction of RT interference was only marginally significant, but in the same direction as in Experiment 1: RT interference increased with relative salience. Also, the interaction between distance and relative salience in model 4 was only marginally significant. Thus, model 2 with the single predictor 'distance' fits best. Overall, less salient color distractors do also capture attention, though the contribution of relative salience was not reliable. Because the interaction was insignificant, no simple slopes were calculated for the data subset with less salient distractors.

With more salient (color-defined) distractors, the mean RT was 723 ms ($sd = 129$ ms) and the mean interference 31 ms ($sd = 94$ ms). For these distractors, too, RT interference increased with smaller distances (Table 3), with the distance effect being significant (Table 4). This replicates previous results that more salient distractors capture attention. Furthermore, relative salience significantly predicted RT interference by more salient distractors, as model 3 provided a significantly better fit than model 2. However, the interaction in model 4 was non-significant, leaving model 3 as the best account of the data. Because the interaction was non-significant, no simple slopes were calculated for the data subset with more salient distractors.

The final analysis included again the whole data set. The mean RT was 694 ms ($sd = 125$ ms) and the mean interference 23 ms ($sd = 87$). For all data points, with color-defined distractors, distance and relative salience were revealed to be significant predictors of RT interference (see Tables 3 and 4 for the statistical details). Also, as in Experiment 1, the interaction term in model 4 was significant, which again indicates varying impact magnitude of distance on RT interference, dependent on relative salience. But here, too, BIC statistics favor model 3 without the interaction.

The interaction was further investigated by examining the simple intercepts and slopes for the 25% quartile (-24 ms relative salience), 0 ms relative salience, and the 75% quartile (61 ms relative salience). Fig. 4 shows the simple relationships, with all slopes differing significantly from zero (-24 ms: -4.67 , $z = -4.39$, $p < .001$; 0 ms: -6.00 , $z = -6.51$, $p < .001$; 61 ms: -9.34 , $z = -8.34$, $p < .001$). As with the luminance-defined distractors in Experiment 1, color-defined distractors also captured attention, as indicated by the distance effect. Likewise, the influence of distance was again moderated by relative salience between target and distractor.

In summary, with color-defined distractors, too, target selection was influenced by target–distractor distance. This was also true for distractors less salient than the target (replicating the finding of Experiment 1), which indicates that even less salient color-defined distractors captured attention. However, in Experiment 2, the influence of distance on RT interference was significantly modulated by

Table 3
Fixed effects and variance estimates for the relationship between distance, relative salience, and RT interference in Experiment 2.

	Model 1	Model 2	Model 3	Model 4
<i>Less salient distractors</i>				
Fixed effects				
Intercept	9.81 (2.75)	9.73 (2.81)	9.47 (2.89)	9.43 (2.91)
Distance		−3.79 (1.21)	−3.79 (1.21)	−3.83 (1.21)
Relative salience			0.10 (0.06)	0.10 (0.06)
Distance × Relative salience				−0.07 (0.04)
Random effect				
Participant	59.97 (7.74)	65.31(8.08)	72.04 (8.49)	73.52 (8.57)
<i>More salient distractors</i>				
Fixed effects				
Intercept	30.46 (3.24)	30.45 (3.30)	30.97 (3.19)	30.94 (3.20)
Distance		−8.99 (1.26)	−8.94 (1.26)	−8.95 (1.26)
Relative salience			0.20 (0.05)	0.20 (0.05)
Distance × Relative salience				−0.05 (0.03)
Random effect				
Participant	108.52 (10.42)	115.71 (10.76)	103.62 (10.18)	104.46 (10.22)
<i>Whole data set</i>				
Fixed effects				
Intercept	22.97 (2.86)	22.97 (2.93)	19.68 (2.82)	19.70 (2.84)
Distance		−6.79 (0.90)	−6.82 (0.90)	−6.00 (0.92)
Relative salience			0.20 (0.03)	0.20 (0.03)
Distance × Relative salience				−0.05 (0.01)
Random effect				
Participant	106.92 (10.34)	113.25 (10.64)	100.40 (10.02)	102.05 (10.10)

Note. Predictors were centered as stated in the analysis section. Coefficients (standard errors) are reported for fixed effects and variance estimates (standard deviations) are presented for random effects.

relative salience only when the whole data set was considered. Presumably, the reason for the non-significant modulation in the subset of data for less salient distractors lies in the stimuli presented in Experiment 2. Compared to Experiment 1, the distribution of relative salience values was different, that is, the range was more restricted, with fewer pairs falling into the extreme range of the target being much less salient the distractor – thus reducing the variation of interference for the subset of less salient distractors.

From the fact that the best-fitting regression models were different for Experiments 1 and 2 (with luminance- and color-defined distractors, respectively), the question arises whether the strength of attention capture would also be influenced by the distractor dimension, that is: does the distractor dimension (luminance vs. color) modulate the effect of distance on RT interference? To examine this, we collapsed the data of both experiments and calculated the hierarchical linear models with the fixed effects ‘distance’ (centered), ‘relative

salience’ (centered), ‘distractor dimension’, and all possible interactions. As in the previous analyses, predictors were included stepwise and significance was assessed by comparing models with χ^2 -tests. Statistical tests were conducted on $N = 29,660$ level-1 observations (relative salience × distance × experiment) and $N = 34$ level-2 groups (participants). Distance was revealed a significant predictor of RT interference ($\beta = -17.38$, $\chi^2 = 202.82$, $p < .001$), as were relative salience ($\beta = 0.54$, $\chi^2 = 266.88$, $p < .001$), experiment ($\beta = -15.04$, $\chi^2 = 10.53$, $p = .001$), the interaction between distance and relative salience ($\beta = -0.07$, $\chi^2 = 40.03$, $p < .001$), the interaction between distance and experiment ($\beta = 5.81$, $\chi^2 = 21.63$, $p < .001$), and the

Table 4
Hierarchical linear model comparison for Experiment 2.

Model	χ^2	BIC
<i>Less salient distractors</i>		
1		77,192
2	9.81**	77,191
3	2.86†	77,197
4	3.53†	77,202
<i>More salient distractors</i>		
1		116,796
2	50.48**	116,755
3	14.82**	116,749
4	2.50*	116,755
<i>Whole data set</i>		
1		194,341
2	57.06**	194,294
3	65.06**	194,200
4	14.03**	194,234

Note. BIC: Bayes Information Criterion.

† $p < .10$.

** $p < .01$.

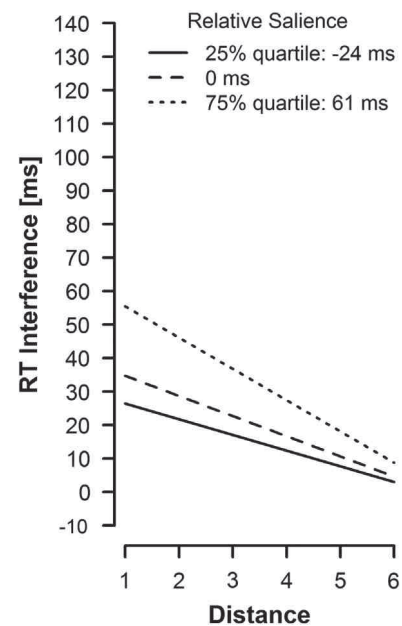


Fig. 4. Interaction effect in Experiment 2. RT interference as a function of target-to-distractor distance (i.e., the number of non-targets between target and distractor), conditional on relative salience (distractor minus target). Simple slopes are depicted for different relative salience values of the whole data set.

interaction between relative salience and experiment ($\beta = -0.17$, $\chi^2 = 23.22$, $p < .001$). The three-way interaction was not significant ($\beta = 0.04$, $\chi^2 = 3.24$, $p = .072$). The interaction analysis revealed the distance effect to be the stronger the higher the relative salience was, and to be overall more marked in Experiment 1 than in Experiment 2. The effect of relative salience on RT interference was also stronger in Experiment 1 than in Experiment 2. As for the (modulating) influence of the distractor dimension, the effect pattern indicates that capture was more pronounced (as evidenced by the stronger distance effect), and that the RT interference increased more strongly with relative salience, when the distractor was luminance-defined rather than color-defined.

4. General discussion

We found singleton distractors less salient than the target to capture attention. The size of RT interference in the distractor search paradigm was dependent on the distance between target and distractor, and the strength of this relationship was modulated by the stimuli's relative salience. We observed RT interference to be the greater the closer both stimuli were located to each other and the more salient the distractor was compared to the target. The question at issue in the present study was whether the interference (costs) caused by less salient distractors are attributable to spatial attentional capture or, alternatively, to non-spatial filtering mechanisms. To address this, we took the influence of distance on RT interference as an indicator of spatial attentional capture and manipulated distance and salience parametrically in two experiments with different distractor dimensions (luminance and, respectively, color).

4.1. Distance effect as indicator for attentional capture

Non-spatial filtering costs are assumed to (i) reflect a delay in the allocation of attention to the target owing to parallel processing of both stimuli for their identity, and (ii) to be non-spatial in nature (Folk & Remington, 1998, 2006). Thus, any spatial modulation, such as an influence of distance between target and distractor on RT interference, would rule out (by definition: non-spatial) filtering costs as sole source of RT interference.

While the presence of a distance effect excludes non-spatial filtering costs, it is not intuitive that it would indicate attentional capture at the same time, especially given that larger RT interference is associated with smaller distances. To understand why attentional capture may be inferred from this influence of distance on RT interference, it is helpful to take a more detailed look at the chain of processing in the search task and to draw on theories of attentional distribution.

In the distractor search paradigm, performance involves a chain of decisions that have to be made until a response can be given (Wolfe, 1994; Wolfe & Van Wert, 2010; Zehetleitner, Rangelov, & Müller, 2012). The search process starts with the selection of the first item (which can be regarded as a decision amongst all items). In a second step, the selected item has to be identified and, if it is recognized as a target, a decision about the correct response has to be made. If the first identified item is the distractor, attention needs to be disengaged and a second selection has to be executed, after which the chosen item has to be identified and the respective response has to be selected. In this decision chain, all processes that contribute to the first selection can be considered as pre-selective and all subsequent processes as being post-selective.

The distribution of attention, when it is directed at a certain location, is described by Localized Attentional Interference (LAI) theory (Mounts, 2000, 2005; Mounts & Gavett, 2004). On this theory, enhanced processing within the focus of attention is associated with a ring of suppression around the attended location (a "Mexican-hat"-type function; e.g. Caparos & Linnell, 2009; Hodgson, Müller, & O'Leary, 1999; Müller et al., 2005), as a result of which items located

within this ring are more difficult to detect. With regard to the distractor search paradigm, this implies that if attention was first focused on the distractor location, it would be more difficult to subsequently select the target when it is located nearby the distractor compared to when it is some distance away. Finding such an influence of target-distractor distance on RT interference thus indicates that attention must have been allocated to the distractor – because, had it been allocated immediately to the target instead of the distractor, no second selection would have been necessary and hence no distance effect would have arisen. In other words, the distance effect in the distractor search paradigm arises post-selectively (i.e., after the first selection). With regard to the distance modulations revealed in the present study, this implies that there was attentional capture not only for distractors more salient than the target, but also for less salient distractors; that is, the latter capture attention, too, rather than merely producing non-spatial filtering costs.

LAI theory is based on the assumption that attention visits the distractor and target location serially. This is in accordance with the idea of a decision chain building up the selection process (Wolfe, 1994; Wolfe & Van Wert, 2010; Zehetleitner, Rangelov, et al., 2012). However, there are other theories that predict a distance effect as a consequence of attentional capture while assuming a parallel processing architecture. In the realm of the attentional capture literature, Caputo and Guerra (1998), for instance, suggested target and distractor processing to take place in parallel, but once the distractor has captured attention, a spatial filtering mechanism in the form of a ring of suppression slows down parallel target identification. However, with this processing architecture, too, attentional capture by the distractor is the cause of the distance effect, that is, target selection is delayed when it is close to the distractor, even if its processing started in parallel with distractor processing.

Irrespective of the processing architecture, the distance effect resulting from a first distractor selection was modulated by the relative salience between target and distractor: it was more pronounced for distractors of higher salience than for distractors of lower salience compared to the target. One way to explain this modulation is based on the assumption of proportionate capture and no-capture events (Zehetleitner et al., 2013). In order to demonstrate that the finding of a distance effect modulation by relative salience can indeed be explained by the proportion of capture trials, we describe the linkage between the proportion of capture events and the distance effect step by step.

The basic assumption is that relative salience between target and distractor determines the proportion of capture events (Zehetleitner et al., 2013): the more salient the distractor is compared to the target, the more likely it is the first item to be selected. Now, RT interference is calculated as the RT on distractor-present trials minus the RT on target-only trials. Yet, RTs on distractor-present trials are dependent on whether or not the distractor captures attention. On the idea that performance involves a chain of discrete decision processes, RTs on non-capture trials would be equivalent to those on target-only trials, because in both cases, the target is the first item to be selected and no further (second) selection would be involved. In contrast, RTs on trials on which capture occurred would be longer as they include the time required to disengage attention from the initially selected distractor and to select and further process the second, target item. According to the Localized Attentional Interference (LAI) account (Mounts, 2000, 2005; Mounts & Gavett, 2004), the time required for the second selection is dependent on the distance of the target from the distractor. Consequently, a distance effect manifests only when attention is first captured by the distractor. If the proportion of such capture trials is high, a greater number of distance-dependent second-selection processes would contribute to the RT interference effect, and vice versa when the proportion of capture trials is low. From this it follows that a high proportion of capture trials results in a marked overall distance effect, whereas a low proportion gives rise

to a lesser effect. According to Zehetleitner et al. (2013), the proportion of capture events is high when the salience of the distractor relative to that of the target is high, and it is low when relative salience is low. Thus, relative salience and the size of distance effect are directly related, and the assumption of proportionate capture events can explain the modulation of the distance effect by relative salience.

4.2. Conflicting findings

However, not all previous studies that reported RT in a distractor search paradigm to be modulated by the spatial distance between target and distractor, agree on what exactly the modulation looks like. In the present study, as well as in previous studies (Caparos & Linnell, 2009; Caputo & Guerra, 1998; Eriksen & St. James, 1986; Hickey & Theeuwes, 2011; Hodgson et al., 1999; Mounts, 2000, 2005; Mounts & Gavett, 2004; Müller et al., 2005; Theeuwes et al., 2004; Zehetleitner et al., 2009), interference became larger, or RT slower, the closer target and distractors were located to each other.

Becker (2007), who also posed the question of whether the RT increase in the distractor search paradigm resulted from non-spatial filtering or attentional capture, found a distance-dependent modulation in the opposite direction, with longer RTs for greater distances and faster RTs for shorter distances. She concluded that the RT increase is primarily attributable to non-spatial filtering costs and that the distance effect is induced by a small amount of capture trials. However, Becker's (2007) error rates pointed in the reverse direction to the RT pattern, with fewer errors for greater distances and more errors for closer placements. This speed-accuracy trade-off (which, if corrected for, might produce the opposite pattern) makes her results difficult to interpret. Another reason for the divergent results between Becker's (2007) and our study might be the dissimilar display density. Becker (2007) used sparse displays, whereas we used displays with greater stimulus density. It is known that processing is different in dense compared to sparse displays (Bravo & Nakayama, 1992), and that effects of salience are greater with denser displays (Nothdurft, 2000; Rangelov, Müller, & Zehetleitner, submitted for publication).

4.3. Theories of attentional selection

The fact that less salient distractors, too, can capture attention (albeit less frequently than more salient distractors) is at variance with a seminal theory of salience-based selection which holds that only the most salient item in the visual field can capture attention: "We assume that the initial shift of attention [is] to the most salient singleton" (Theeuwes, 2010, p. 80). Although this account is controversial, it has hitherto mostly been challenged by evidence based on the use of a different paradigm and focusing on the issue of top-down controlled as contrasted with bottom-up guidance of attentional allocation (Bacon & Egeth, 1994; Eimer & Kiss, 2008; Folk et al., 1992; Kiss, Jolicoeur, Dell'Acqua, & Eimer, 2008; Müller et al., 2009; Zehetleitner, Goschy, et al., 2012). The present findings, however, were obtained using the very same – distractor search – paradigm, and can neither be explained by top-down control nor by simple salience-based selection as envisaged in this theory (Theeuwes, 2010).

Instead, we explain our results of capture by less salient distractors within the sequential sampling model of salience-based selection (Zehetleitner et al., 2013), which is in general agreement with existing salience-based models of visual search (Itti & Koch, 2001; Koch & Ullman, 1985; Wolfe et al., 1989). However, going beyond these models, our framework explicitly specifies the time course of salience-based attentional selection. It takes into account the noisy build-up of activation on the selection-guiding salience map – and because of this noisy accumulation of sensory evidence, the actual salience value associated with each stimulus in the field varies around its mean of (overall) 'true' salience. Accordingly, the most salient item is selected only with a certain probability, and by implication, less salient stimuli may also be

selected with some probability – which allows for attentional capture by distractors less salient than the target.

In more detail, the sequential sampling model of salience-based selection (Zehetleitner et al., 2013) assumes that sensory evidence for all items in the field is accumulated until a threshold is reached and a selection decision is triggered. The drift rate, with which sensory evidence for each item is accumulated, is determined by the salience of the respective item (Zehetleitner & Müller, 2010). Relative salience (i.e., the drift rate difference between the target and the distractor) and noise in the accumulation process over time produce variation in the map output, based on which attention is allocated to a location. Consequently even distractors less salient than the target may reach the selection threshold before the target and thus, capture attention in a certain proportion of trials. Following the logic of this stochastic salience model, the probability of the distractor exceeding the threshold prior to the target diminishes as its salience, relative to that of the target, decreases.

In accordance with this model are the results of singleton-distractor studies that monitored eye movements, showing that distractors less salient than targets decrease oculomotor accuracy especially for slow-latency saccades (Van Zoest & Donk, 2005; Van Zoest, Donk, & Theeuwes, 2004). These findings, too, indicate that the time course of selection is crucial, whether a distractor does or does not capture attention.

4.4. Parametric manipulations

Hitherto, attentional capture has mostly been investigated using binary salience manipulations and dichotomically examining whether or not attentional capture occurred (De Fockert et al., 2004; Donk & Van Zoest, 2008; Folk et al., 1992; Hickey et al., 2006; Lamy, Leber, & Egeth, 2004; Theeuwes, 1992). While this approach has the advantage of being simple and providing a good starting point for examining the issue, it entails the possibility of overlooking, or failing to recognize, relationships that are not represented by a binary sample of the variable investigated. That is to say: if the distractor is varied in two steps (or even held constant), conclusions about the relationship between salience and attentional capture are necessarily oversimplified. As recent studies demonstrate, cognitive relationships are more complex and stochastic in nature (Gold & Shadlen, 2007; Vul, Hanus, & Kanwisher, 2009). Even though it is implicitly accepted that the relationship between salience and attentional capture is a gradual one, capture by less salient distractors had not been demonstrated until recently (Zehetleitner et al., 2013) and, thus, existing salience-based selection models had not been challenged in this respect. To prevent the drawing of false or restricted conclusions, we therefore advocate the use of parametric manipulations and to pose questions about probabilities and proportions, rather than simply the presence versus absence of a certain phenomenon.

We only manipulated the bottom-up salience parameter parametrically, and the stochastic salience model explains our results also only from a bottom-up perspective. Yet, it is possible to incorporate top-down control into the model by introducing an impact on, for instance, the (drift) rate of sensory evidence accumulation, which can thus modulate the probability of capture. Although this is not implemented in the model as yet, a mechanism such as 'target dimension weighting' (Found & Müller, 1996) could be one possibility of top-down influence as weighting operates already at an early processing stage (Kuhbandner & Zehetleitner, 2011; Melloni, Van Leeuwen, Alink, & Müller, 2012; Müller & Krummenacher, 2006; Töllner et al., 2012; Zehetleitner, Goschy, et al., 2012; Zehetleitner, Krummenacher, Geyer, Hegenloh, & Müller, 2010; Zehetleitner & Müller, 2010). A mechanism for combining salient and behaviorally relevant information in a joint map for stimulus selection is at the heart of Gottlieb's (2007) notion of a 'priority map'. Furthermore, parametric manipulations that influence mechanisms of top-down

control might provide new insights into the occurrence of attentional capture, as they have done in response conflict research (Durstun et al., 2003; Forster, Carter, Cohen, & Cho, 2011).

5. Conclusion

The present study demonstrates that in the distractor search paradigm, where target and distractor are simultaneously presented, distractors that are more salient than the target capture attention; importantly, however, less salient distractors too can capture attention (although the proportion of capture events is smaller). Only distractors that are far less salient than the target fail to capture attention. The present study cannot completely rule out non-spatial filtering costs for less salient distractors, but it can exclude the notion that non-spatial filtering is the only mechanism responsible for RT interference (caused by less salient distractors).

In terms of bottom-up attentional capture by less salient distractors, we conclude that non-spatial filtering alone is not sufficient to explain RT interference in the distractor search paradigm. Rather, the occurrence of spatial capture is proportionate, with the relative salience between target and distractor determining the size of this proportion. As a consequence, attentional capture by less salient distractors relative to the target is possible and stochastic in nature, as we have demonstrated here.

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**Distribution analysis of reaction time interference: Speeded target selection after
attentional capture**

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Abstract

Interference in the distractor search paradigm, when a distractor is present compared to absent, is a frequently reported phenomenon. However, the source of this interference is unclear and debated. While some authors claim the additional time is the result from spatial attentional capture, others think that attentional deployment to the target is slowed due to filtering processes. By contrast, the second target selection after attentional capture by the distractor has hardly been investigated. To discriminate between spatial capture and slowed target selection and to investigate the second target selection, we qualitatively analyzed the distribution of reaction time and saccadic interference. Predictions about the distribution were generated by an accumulator race model and were qualitatively tested by two reaction time and one eye movement experiment. The results favor attentional capture as source for interference. Moreover, once attention was captured, the second target selection was faster than when no distractor was present. This result is explained by an immediate selection of the second most salient item. In conclusion, attentional capture by a distractor can slow target selection in some cases and speed it in other.

Keywords: attentional capture, filtering, accumulator race model, second selection

To move around efficiently in our environment, humans must behave goal-oriented, which requires filtering out distracting stimuli. Imagine driving down the road, looking for the small sign designating the destination. While searching for it, i.e. voluntarily directing attention to potential target signs, one disregards other stimuli at the roadside to achieve the goal, namely finding the destination. But if one ignored all other stimuli impinging on the sensory organs completely in this situation, it could be life-threatening, for instance if one misses a red light or the pedestrian crossing the street in front of one. This means, distraction or involuntary capture of attention on some occasions serves goal attainment in the long run and can therefore be supporting, although contradictory to the current goal. The question that has been asked frequently in the literature by now is ‘what characteristics of a stimulus make it capture attention of an observer automatically?’.

The Distractor Search Paradigm

In order to find an answer to this question, many studies used the distractor search paradigm (Theeuwes, 1992). In this paradigm, a task-relevant target singleton and an irrelevant distractor singleton (both carrying unique features compared to all other stimuli) are surrounded by homogeneous non-target stimuli. For instance, a display containing a gray tilted bar predefined as target and a bright vertical bar as distractor, amongst gray vertical non-target bars. The task is to search for the target stimulus while ignoring the possibly present distractor. A typical (although debated) result is an increase in reaction time (RT) when a more salient distractor than the target, i.e. a more conspicuous distractor than the target, is present compared to when it is absent (Bacon & Egeth, 1994 Exp. 1; Becker, 2007; de Fockert, Rees, Frith, & Lavie, 2004; Hickey, McDonald, & Theeuwes, 2006; Hickey, Van Zoest, & Theeuwes, 2009;

Hickey & Theeuwes, 2011; Hodson, Mevorach, & Humphreys, 2009; Kumada & Humphreys, 2002; Kumada, 1999; Lamy & Yashar, 2008; Lavie & de Fockert, 2006; Leber, 2010; Müller, Geyer, Zehetleitner, & Krummenacher, 2009; Theeuwes, 1991, 1992; Töllner, Müller, & Zehetleitner, 2012; Wykowska & Schubö, 2010; Zehetleitner, Müller, & Proulx, 2009).

The Source of Reaction Time Interference

If RT interference evoked by a salient distractor occurs, the source of this interference is not yet clearly identified and is still debated. Some authors interpret RT interference in the distractor search paradigm as spatial attentional capture, that is attention visits the distractor location before the target location (Hickey & Theeuwes, 2011; Theeuwes, 1992, 2010; Zehetleitner, Koch, Goschy, & Müller, 2013). Others claim that RT interference reflects non-spatial filtering costs that result from the concurrent processing of another salient stimulus (Becker, 2007; Folk & Remington, 1998, 2006; Wykowska & Schubö, 2010). Critically, according to these latter authors, attention is NOT directed to the distractor location before oriented to the target location. Such filtering costs are assumed to arise from non-spatial competition between both stimuli (Wykowska & Schubö, 2010) or parallel identification (Folk & Remington, 2006). Although not explicitly mentioned by the authors of these studies, to our understanding, this is similar to what the theory of Biased Competition (Desimone & Duncan, 1995) describes: simultaneously presented objects compete for representation, this competition being biased by bottom-up factors or top-down attentional control. However there are two important differences between the notion of filtering and Biased Competition. First, Biased Competition postulates spatial modulation of competition with stronger competition for close items. Second, Biased Competition explains both in the distractor search paradigm, capture by

the distractor, in case the distractor wins the competition and no capture, in case the target wins the competition. Filtering on the other hand assumes only the case that the target is selected first. Because the question at hand is whether or not the distractor captures attention and Biased Competition does not make discriminable predictions here, we will speak of attentional capture and non-capture accounts, the former including first selection of the distractor and the latter including filtering and competition mechanisms without first selection of the distractor.

Predictions about Means and Distributions

Folk and Remington (1998) state “the visual search paradigm used to measure attentional capture confounds two potential sources of disruption – filtering costs and shifts of spatial attention.” (p.849). This is certainly true if mean RT’s of experimental conditions are analyzed, but as Cousineau and Shiffrin (2004) or Balota and Yap (2011) point out, some theories make the same predictions about mean performance, but differ in their predictions when distributions are considered. For RT interference in the distractor search paradigm, non-capture accounts as well as capture accounts would predict RT interference when a distractor is present and this interference to be higher with increasing salience of the distractor relative to the target (Zehetleitner et al., 2013). Distribution analyses for this paradigm have so far only been conducted for eye movements (Donk & Van Zoest, 2008; Godijn & Theeuwes, 2002; Van Zoest, Donk, & Theeuwes, 2004; Van Zoest & Donk, 2005, 2008). To derive predictions from the theoretical accounts about RT interference distribution, we take a step back and look at the processing architecture of capture and non-capture trials.

Both possible sources of RT interference, attentional capture and non-capture costs, differ in their underlying processing architecture. With respect to attentional capture, because of

fluctuations in attentional control (Leber, 2010), it is unrealistic to assume attentional capture to occur in every trial, but rather in a proportion of trials, the size of which is dependent on the distractor's salience relative to the target's salience (Zehetleitner et al., 2013). For non-capture costs, there is one selection for distractor absent and present trials, namely target selection. For attentional capture, there is one (target) selection for distractor absent trials, but two possible processing ways for distractor present trials: either there is only the target selection if no attentional capture occurred, or in case of attentional capture, there are two selections, namely the distractor selection and the subsequent target selection. Considering the fact that attentional capture trials, comprising two selections, are slower than no-capture trials where attention travels immediately to the target, RT interference should increase with RT latency, as the proportion of capture trials becomes larger. Although comprehensive reports on RT interference as a function of RT latency are pending, one study touched this issue and reported a trend for RT interference to increase over quartiles (Belopolsky & Theeuwes, 2010). Since the proportion of capture trials is also dependent on relative salience between target and distractor (Zehetleitner et al., 2013), this effect of increasing RT interference with increasing RT latency should be even more pronounced with higher distractor salience relative to the target.

For non-capture accounts, predictions about RT interference distribution are more difficult to establish and because attentional selection in the distractor search paradigm can be regarded as a decision between the target and the distractor (Zehetleitner et al., 2013), we used the accumulator race model (Usher & McClelland, 2001) as basis to generate more precise predictions for capture and non-capture accounts. The architecture of these accumulator models resembles the one of the model described in Zehetleitner et al. (2013): sensory evidence for the

target and the distractor is accumulated over time, by two accumulators with a drift rate that is determined by stimulus salience. Each accumulator is racing towards the same selection threshold, the first hitting it denoting the selected stimulus – target or distractor. In this model, non-capture accounts are implemented in restricting the race outcome in a way that the target always wins, i.e. it hits the selection threshold before the distractor. For capture accounts, there is no such restriction and distractor or target can hit the threshold first resulting in a capture trial for the former and non-capture trial for the latter.

The core assumption of non-capture competition accounts is that the target selection is slowed when a distractor is present compared to when it is absent. We implemented this in the race model by reducing the drift rate of the target when a distractor is present compared to the drift rate of trials where the target is presented alone. For capture accounts, the drift rate of the target was the same in distractor present and absent trials, but for capture trials, costs were added for the distractor selection and the subsequent disengagement process from the distractor. In addition, we modeled two alternatives for the second (target) selection.

The second selection after attentional capture is largely unexplored, but on the basis of our computational model, one can derive two alternatives of how it could proceed. First, after attention was captured by the distractor, i.e. the distractor accumulator hit the threshold, the target accumulation continues as before and it is selected at the time the target accumulator hits the threshold. In this case one would simply wait for the target to reach the threshold and the target would be selected at the same time it would be selected without a distractor being present. If a distractor is present, it always takes longer (in case of capture) or equally long (in case of no capture) to select the target compared to when the target is presented alone; that is RT

interference is always positive or zero. Second, an alternative for the second target selection could be a decrease of the selection threshold to the level of the accumulated evidence of the target at the time attention has disengaged from the distractor. In this case, one would not have to wait for the second selection until the accumulation of target evidence reaches the threshold, but simply take the next salient item. Because one knows that there are only two salient stimuli in the field, one can select the second salient element (the target) immediately. In other words, attentional capture by the distractor could expedite target selection if the sum of capture costs and disengagement costs is less than the time target selection would cost without a distractor. If one considers the positively skewed selection time distribution of a given drift rate, the benefit should become larger with longer selection times, i.e. RT latencies (see Figure 1 for illustration). In other words, in some cases, namely when the target selection time is longer than the time it costs to select the distractor and disengage from it, a distractor can expedite RTs instead of prolong them, assuming that the selection threshold is lowered for the second selection and attention immediately selects the next most salient stimulus. In terms of RT interference, this would mean that RT interference becomes negative.

Although the pattern of RT interference is deducible from theory, as stated above, implementations of all three theories were run to generate predictions for the distribution of RT interference and thereby test the race model behavior. These predictions are depicted in Figure 2. The first simulation depicts the prediction of non-capture accounts, the second simulation represents predictions of capture accounts with a fixed selection threshold, and the third simulation shows predictions for capture accounts with a variable selection threshold that adapts

to the accumulated evidence of the target at the time where attention has disengaged from the distractor location.

As can be seen from Figure 2a, non-capture accounts would predict overproportionally increasing RT interference with increasing percentile of RT latency. Capture accounts on the other hand would predict an initial increase of RT interference and a decrease in later percentiles (Figures 2a and 2b). Whereas a capture model with a fixed threshold for the second target selection predicts RT interference always to be in the positive range, a capture model with a variable selection threshold predicts RT interference to drop into the negative range in the last percentiles. In other words, a model with a variable selection threshold predicts faster RTs when the distractor is present compared to when it is absent for slow RT latencies. In these cases the distractor expedites RT instead of slowing it. As stated before, although counterintuitive, this is the case if the cost the distractor evokes plus the time it takes to disengage attention from it is overall shorter than the time it takes the target accumulator to reach the threshold as it was set for the first selection without variable adaptation after the first selection.

To recapitulate, non-capture and capture accounts make the same predictions about mean RT interference, yet simulations suggest different qualitative predictions for the distribution. Therefore, distribution analysis constitutes a means to distinguish between spatial shifts of attention and filtering costs in the distractor search paradigm. Hence, the statement of Folk and Remington (1998) that the distractor search paradigm could not distinguish between both options is not valid.

Study Goal

Goal of this study was to investigate the cause of RT interference in the distractor search paradigm and the second target selection after attentional capture by the distractor. Predictions of capture and filtering (i.e. non-capture) theories do not make discriminable predictions about mean interference, but they do make different predictions about the distribution of RT interference. We take this advantage of distribution analysis to decide between the occurrence of capture and non-capture in the distractor search paradigm and to investigate the second target selection. To this end we conducted two reaction time experiments and one eye tracking experiment. In experiment 1, which was a RT experiment, the target was orientation defined and the distractor, which could be present, was color defined. In experiment 2, we tested for generalization across dimensions and defined the target again in the orientation dimension, but the distractor in the luminance dimension. Although distribution analyses were so far mainly carried out with eye movement data (Donk & Van Zoest, 2008; Godijn & Theeuwes, 2002; Van Zoest et al., 2004; Van Zoest & Donk, 2005, 2008), none of these studies looked at saccadic latency interference analogue to RT interference, that is saccadic latency of correct trials (first fixation on target) when the distractor is present compared to when the target is presented alone. That is, although a saccade can be carried out correctly to the target, attention could be covertly captured beforehand. This should be visible in the saccadic latency. In experiment 3, we therefore recorded eye movements in the distractor search paradigm to test (i) whether there occurs similar interference as in RT experiments and (ii) whether the distribution of this interference is the same as the costs in the RT experiments, i.e. whether attention was spatially captured or saccadic latency merely slowed. The goal of this article is to discuss the important qualitative properties of RT interference distribution.

Experiment 1

Goal of experiment 1 was to test whether RT interference in the distractor search paradigm is the result of spatial attentional capture or of non-capture filtering processes. To this end, salience of an oriented target and a colored distractor was parametrically varied and distribution of RT interference across RT latency was analyzed and compared with the simulated predictions (Figure 2).

Methods

The methods were as in Zehetleitner et al. (2013).

Participants. Eighteen paid (€ 16) volunteers took part in experiment 1. One had to be excluded because of too many outliers (more than 2.5 *sd* above the mean) and one had to be excluded because of technical problems. The remaining 16 participants had a median age of 26 (range 20-49) years, four of them male, 15 dextral and with visual corrected-to-normal acuity and normal color vision.

Stimulus presentation and data acquisition. The experiment was conducted in a sound-insulated booth, and was controlled by a program purpose-written in C++. Stimuli were presented on a 20" Mitsubishi Diamond Pro 2070^{SB} monitor at a resolution of 1,280 × 1,024 pixels and a refresh rate of 100 Hz; viewing distance was approximately 73 cm. Participants responded using their left and right index fingers, respectively, to press buttons 2 and 8 of the numeric keypad of an Empirisoft DirectIN keyboard. RTs and response accuracy were recorded online.

The display consisted of 39 vertical broken gray bars presented on black background and arranged equidistantly on three imaginary concentric circles around the center of the screen.

Radii of stimuli circles were 1.18° , 2.20° , and 3.06° of visual angle, respectively. The bars were $0.71^\circ \times 0.16^\circ$ in size and had a 0.08° -gap randomly located at the top or bottom of each bar. Targets differed from non-targets in orientation (9, 10, 11, 16, and 45 from the vertical), and distractor differed from non-targets in color with different shades of red (RGB 173/107/114, 181/103/110, 185/97/104, 210/78/87, 252/0/21). All stimuli were matched for luminance ($16.2 - 17.3 \text{ cd/m}^2$). A pilot experiment was conducted to ensure that target and distractor salience was sufficient for these stimuli to ‘pop out’ from the search array, i.e., their associated detection times were independent of the number of non-targets in the display.

Design and procedure. Two 1-hr sessions were carried out on consecutive days, at the same time of day. The first part of each session was the distractor experiment; the second part was a short experiment to measure stimulus salience (for the latter, see *Stimulus Salience Measurement*). For the distractor experiment, factors manipulated within participants were distractor presence (present vs. absent), target salience (five levels), and in case of distractor presence, distractor salience (five levels). A target was present on all trials; distractors occurred randomly in 50% of the trials. Each target and distractor salience combination occurred equally often. A target and a distractor (when present) could be presented only at one of the 12 positions of the second (intermediate) circle of the stimulus display; their exact positions were chosen randomly, with the constraint that the target and distractor could never share the same location. Importantly, relative target-distractor salience was randomized within trial blocks. Participants completed 20 blocks of 50 trials each day, yielding a total of 2,000 trials.

Each trial started with a white fixation dot, presented for a duration uniformly distributed between 900 and 200 ms, that was superseded by the search display which remained present until

response (Figure 3a). Participants were instructed to indicate, as quickly and accurately as possible, the gap location (top or bottom) of the target by pressing the 8 or 2 button, respectively. In case of an error, visual feedback was provided, followed by an additional 500-ms blank screen before the next trial. At the end of each block, participants were informed about their mean RT and error rate.

Stimulus salience measurement. Because salience is a psychological construct, rather than a physical given, we used a behavioral measurement of salience, which was collected in a short experiment after each session of the distractor experiment. Stimuli were the same as in the distractor experiment. All target orientation and distractor color contrasts from the distractor experiment (Figure 3b) were presented as (to-be-detected) targets randomly intermixed with target-absent displays (as in the distractor experiment, targets never occurred on the outer circle). The design was 2 (target presence vs. absence) \times 2 (dimension color vs. orientation) \times 5 (contrast) factorial. Participants' task was to indicate the presence of an orientation or color target via button press; response was to be withheld if no target was present. Four blocks consisting of 80 trials were performed each day, yielding a total of 640 trials and 32 trials per contrast condition. The stimulus display was presented until response or a maximum duration of 1,200 ms.

Using these detection RTs as our measure of stimulus salience, we calculated the relative salience between stimuli in the distractor experiment by subtracting distractor salience from target salience. For example, if a target was detected at a rate of 350 ms and a distractor at one of 400 ms, then their salience difference was considered to be -50 ms. Note that items of higher

salience are associated with shorter RTs; negative values of relative salience indicate a distractor less salient, and positive values a distractor more salient than the target.

Data analysis. The first 20 trials (first 10 trials of the stimulus salience measurement) of each session and the first 3 trials of each block served as practice trials and were excluded from analysis. Of the remaining trials, only correct-response trials were used for analysis (distractor experiment: 96.3%; stimulus salience measurement: 99.2%), excluding RTs that were longer or shorter than 2.5 *sd* of the participants' mean RT in the respective condition (distractor experiment: 2.7%, salience measurement: 1.3%).

Distributions of RT interference were calculated according to the vincentizing procedure (Ratcliff, 1978) for each relative salience (target salience - distractor salience) condition separately. In a first step, RTs of each participant for distractor absent and present trials were rank ordered and percentile RTs were determined for both trial types. This step can be displayed in a cumulative distribution function (CDF), which plots probabilities for the respective or a faster RT. In the second step RT interference was calculated by computing the horizontal difference between corresponding RT percentiles of distractor absent and present trials. This horizontal difference, i.e. RT interference can be plotted as a function of percentile. Finally, percentile RT and interference were aggregated across participants. All data analysis was carried out with R (R Development Core Team, 2010).

Results and Discussion

Parametric salience manipulation revealed a good range of distractors more and less salient than the target with a greater number of distractors more salient than the target. The most salient

distractor was 99 ms more salient, i.e. faster detected, than the target and the least salient distractor was 87 ms less salient, i.e. slower detected, than the target (Figure 4).

Results of the distribution analysis are presented in Figures 5 and 6. Because ways of presenting results of distribution analyses have varied in the literature and readers might be more familiar with one or the other way, we deliberately present the data in two different formats. In the cumulative distribution functions it is already prominent that trials in which the target was presented alone are faster in the last percentile than trials where the target was presented together with a distractor. RT interference, which is the horizontal difference between percentiles of target alone and target plus distractor trials, is easier to understand from Figure 5 and 6. These Figures show that distribution of RT interference looks qualitatively similar to the simulated predictions of the capture model with a variable selection threshold. Interference increases with percentile and drops in the last or second last percentile, in some cases even into the negative range. Longer RT latencies for a given drift rate are the result of noise (Figure 1) and as we hypothesized, for a given target-distractor pair, i.e. two given drift rates, interference decreases. The increase of RT interference is the more pronounced the more salient the distractor is compared to the target. Because Figure 6 depicts RT interference as a function of percentile, RT latencies are hidden. Figure A1 in the appendix therefore shows RT interference as a function of RT latency. From this figure, it becomes obvious that the dip of RT interference in the last percentile is not the result of longer RTs per se, but is indeed a result of RTs from the right tail of the selection time distribution of one particular drift rate.

Experiment 2

To generalize the results of experiment 1 to another distractor dimension, in experiment 2 the target had to be selected in the presence of a luminance defined distractor.

Methods

Methods of experiment 2 were the same as in experiment 1 if not stated otherwise.

Participants. Seventeen paid volunteers took part in experiment 2. One had to be excluded because of too many outliers. The remaining 16 participants had a median age of 27 (range 20-50) years, five of them male, all dextral and with visual corrected-to-normal acuity.

Stimulus presentation and data acquisition. Stimuli were presented on a 19" View Sonic Graphics Series G 90 fB monitor at a resolution of 1,024 x 768 pixels and a refresh rate of 85 Hz; viewing distance was approximately 57 cm. Participants responded using their left and right index fingers, respectively, to press one of two vertically arranged buttons on a purpose-built response pad. RTs and response accuracy were recorded online.

Radii of stimuli circles were 1.88°, 3.25°, and 4.63° of visual angle, respectively. The bars were 1.13° × 0.25° in size with a gap of 0.13°. Targets differed from non-targets in orientation (7, 8, 9, 14, and 45° from the vertical), and distractors differed from non-targets in luminance (13.8, 14.8, 17.9, 19.4, and 25.5 cd/m² for distractors and 5.25 cd/m² for non-targets).

Design and procedure. Design and procedure was identical to experiment 1 with the exception that the response pad was purpose-built and buttons were therefore not numbered 2 and 8; however they were also vertically arranged.

Baseline salience measurement. Baseline salience measurement was the same as in experiment 1, but instead of colored targets, luminance targets were presented as in the corresponding distractor experiment.

Data analysis. The same trials as in experiment 1 were excluded as practice trials. Of the remaining trials, only correct-response trials were used for analysis (distractor experiment: 96.1%; stimulus salience measurement: 98.8%), excluding RTs that were longer or shorter than $2.5\text{ }sd$ of the participants' mean RT in the respective condition (distractor experiment: 2.6%, salience measurement: 1.1%). Distribution analysis was analogue to experiment 1.

Results and Discussion

The range of salience differences due to parametric manipulation was again wide with the most salient distractor being 85 ms more salient, i.e. faster detected, than the target and the least salient distractor being 127 ms less salient, i.e. slower detected, than the target. Figure 7 gives an overview about all target distractor salience differences.

Results of the distribution analysis are presented in Figures 8 and 9. Overall, results qualitatively resemble those of experiment 1 and are in accordance with the simulated predictions of the capture model with a variable selection threshold. Trials in which the target was presented together with a distractor are for many target distractor pairs faster in the last percentile than trials where the target was presented alone. Distribution of RT interference again follows an inverted U-shape, that is it increases with percentile and drops in the last or second last percentile, again, in some cases into the negative range. The increase of RT interference is the more pronounced the more salient the distractor is compared to the target. The increase is also more pronounced than in experiment 1, which suggests that here, more capture trials

occurred. RT interference presented as function of RT latency (Figure A2) again suggests that the dip in is not the result of longer RTs, but confirms that it is a result of RTs from the right tail of the selection time distribution of one particular drift rate.

Experiment 3

Experiments 1 and 2 indirectly measured capture of covert attention and suggest by means of distribution analysis that attention is indeed captured by the distractor rather than target selection is merely slowed. A closer connected, but still indirect measure of attentional capture is oculomotor capture. Because eye movements and attention are tightly coupled (Deubel & Schneider, 1996), an eye movement to the distractor before to the target is considered to be accompanied by attentional capture. However, as stated above, even if the eyes were not captured by the distractor, attention could be captured before the saccade is executed.

Experiment 3 was therefore designed to apply the same principle of analysis to eye movement data. Saccadic latencies of correct eye movements, i.e. trials without oculomotor capture, were analyzed with respect to distractor presence. The distribution of this “saccadic interference” should resemble the simulated predictions of capture accounts and the distribution of RT interference, if covert capture of attention occurred before the correct eye movement.

Methods

Methods were the same as in experiment 1 if not stated otherwise.

Participants. Eight paid (€ 8) volunteers with a median age of 27 (range 24-46) were recruited for this experiment. Seven of them were female; all were dextral and with visual corrected-to-normal acuity.

Stimulus presentation and data acquisition. Stimuli were generated using a ViSaGe system (Cambridge Research Ltd., UK) with a purpose-programmed Experimental Toolbox for MATLAB (The MathWorks, Inc.). Screen refresh rate was 120 Hz at a screen resolution of 1,024 x 768 pixels. Eye movements were recorded at a sampling rate of 1000 Hz by means of an EyeLink 1000 Desktop Mount eye tracker (SR Research Ltd., Canada) positioned below the display monitor. Participants viewed the monitor from a distance of about 70 cm; to minimize head movements, a chin and forehead rest were used. Eye movements were recorded from the right eye; however, stimulus displays were viewed binocularly.

Gray vertical bars (without gaps) of $0.25^\circ \times 1.35^\circ$ of visual angle were arranged on three imaginary concentric circles (2° , 4° , and 6° of visual angle in radius, with 6, 12, and 18 bars, respectively). A further gray bar occupied the position in the center. Targets differed from non-targets in orientation (22° tilted from vertical to the right or left), and distractors differed from non-targets in color, such that one was more salient (RGB: 252/0/21) than the target and the other one less salient (171/104/110) than the target. A pilot experiment ensured that distractors were faster and slower detected than the target, respectively. All stimuli were matched for luminance ($13.6 - 14.2 \text{ cd/m}^2$).

Design and procedure. The eye-tracking experiment implemented a 2 (distractor absent vs. present) \times 2 (distractor salience high vs. low) factorial within-subject design. To ensure reliable differentiation between target and distractor fixations for data analysis, distractor positioning was restricted in the following way: the target position was chosen randomly out of the 12 possible positions on the middle circle; the distractor position was then chosen to be shifted by three or five positions to either the left or the right from the target position (each in a

random 25% of the distractor-present trials). There were 128 trials per distractor condition. This resulted in 512 trials overall, which were presented in 8 blocks of 64 trials each. Trial presentation order was randomized within blocks (with 32 distractor-absent and 32 distractor-present trials per block).

The task was to make a speeded saccade to the target. Observers were instructed to fixate the fixation cross at the trial start until the appearance of the search display, and then to make a direct saccade to the target, while ignoring the distractor. In case the first saccade went nevertheless to the distractor, participants were instructed to direct the next eye movement to the target. In addition, they were told that after having made a saccade to the target, they should fixate it until the disappearance of the search display.

Each trial started with a fixation cross ($0.5^\circ \times 0.5^\circ$) for 1,000 ms. Then, the search display appeared and remained visible for 1,000 ms. The intertrial interval, in which a black screen was displayed, had a random duration between 700 ms and 1,100 ms. Observers were encouraged to use this interval for briefly closing and resting their eyes, so that they could minimize blinks during the subsequent trial. Additionally, participants could take short breaks between experimental blocks. Prior to each block of trials, a nine-point calibration of the eye tracker was conducted.

Data analysis. Trials were excluded on which search display onset occurred during a saccade or the eye tracker failed to track the observer's pupil (8.7%). Saccadic latencies were calculated as the time between onset of the search display and the initiation of the observer's first saccadic eye movement. Trials with initial saccadic latencies below 80 ms and above 600 ms were excluded (2.7%). The remaining data underwent a drift correction: before the onset of the

search display (i.e., at the end of the fixation cross display), gaze was assumed to have rested on the fixation cross. Thus, for drift correction, the eye's deviation from the fixation cross was subtracted from the subsequent gaze position data for this trial. The initial saccade after search display onset was then assigned to the target or the distractor if it landed within 3° of visual angle of the respective (target or distractor) location.

To calculate saccadic interference, only saccades that immediately went to the target were included in the analysis (74.9%). Of these trials, the difference in saccadic latency was calculated when the distractor was present compared to when it was absent. Distribution analysis was analogue to RT interference in experiments 1 and 2.

Results and Discussion

Results of the distribution analysis are presented in Figures 10 and 11. Distribution of saccadic latency partly resembles the distributions of the RT experiments and the simulated predictions of the capture model with a variable selection threshold. It only partly resembles the predictions, because there is no increase in interference, neither for the more nor for the less salient distractor. However, trials in which the target was presented alone were again faster in the last percentile than trials where the target was presented together with the distractor as indicated by negative interference.

These results suggest that although saccades are executed correctly, covert capture of attention can happen beforehand if the distractor is more salient than the target. Yet, this conclusion has to be treated with caution, because overall, interference was relatively small with a maximum of 13 ms. On the other hand, it is obvious that the distribution qualitatively follows the predictions of a capture model. Despite the fact that distractor interference is not present

during the first percentiles, the benefit due to the distractor is still observable in the slow selection times. This is a hint to covert attentional capture in some cases even before a saccade is correctly executed.

General Discussion

This research was motivated by the question about the source of RT interference, namely spatial attentional capture or filtering. Analysis of mean RTs or mean RT interference cannot distinguish between both sources, because both predict RT interference to increase with stronger salience of the distractor. For the distribution of RT interference however, capture accounts predict interference to increase with RT latency, because capture trials as a result of two selections are slower than no-capture trials. Because the proportion of capture trials grows with stronger distractor salience, the increase of RT interference over RT latency should be enhanced for more salient distractors. That is, the increase of RT interference entails a mixture distribution of non-capture and capture trials with the former constituting the fast, i.e. left end of the distribution and the latter representing the slow, i.e. right end of the distribution. Simulations using a leaky accumulator model (Usher & McClelland, 2001) suggested interference to decrease again in the last percentiles, which gives the prediction about distribution of RT interference an inverted U-shape. These predictions of capture accounts differ qualitatively from predictions of non-capture accounts, which also suggest interference to increase, but in an overproportional fashion without a decrease in later percentiles. Further, predictions of a capture account with fixed selection threshold differed qualitatively from a capture account with variable selection threshold. A fixed threshold implies that when the distractor is present, it always takes longer to select the target as compared to when the target is presented alone. Thus distractor presence

always results in costs, i.e. positive interference. A variable threshold on the other hand speeds up RT when a distractor is present and the target selection is slow: is the time it costs to select the distractor and disengage from it shorter than the selection time of the target, a decrease of the selection threshold after disengagement from the distractor lets the target be earlier selected than when it is presented alone. In this case, interference becomes negative, i.e. the distractor speeds up selection time of the target.

We presented three experiments, two with RT measurement and one with eye-tracking, the results of which qualitatively very much look alike. For more salient distractors, RT interference increased with percentile and dropped into the negative range in the last percentile. For less salient distractors, the increase was not as pronounced as for the more salient distractors or was absent. Both, distributions of interference of more and less salient distractors, is in accordance with the findings of Zehetleitner et al. (2013) that the probability of capture increases with increasing salience of the distractor and that less salient distractors capture attention on a smaller proportion of trials or do not capture attention at all if far less salient than the target (Theeuwes, 1992). The dip into the negative range in the last percentile suggests the second selection to be speeded due to a decrease of the selection threshold. That is, after attention was captured by the distractors, the second most salient item in the visual field is selected immediately, rather than at its normal selection time, which would take longer. Our results are clearly at odds with non-capture accounts that predict interference to overproportionally increase with RT latency.

The intention of this research was to distinguish between capture and non-capture in the distractor search paradigm. To this end, we subsumed both, non-spatial filtering and the special

case of Biased Competition in which the target wins the race, under non-capture accounts. However, this view of Biased Competition was an artificial curtailment of the theory for the purpose of expressing interference as a result of slowing rather than of spatial capture. As full theory, Biased Competition does also account for attentional capture, namely when the distractor wins the competition. The situation is different with non-spatial filtering: this account is a pure non-capture account, although the proposed mechanism is the same as for Biased Competition, namely competition (Wykowska & Schubö, 2010), or parallel identification (Folk & Remington, 2006). On a theoretical level, it is an open question how non-spatial filtering and Biased Competition differ from each other, except that one assumes competition to be non-spatial and the other to be spatial in nature. While for non-spatial filtering, there is no evidence for the mechanism of non-spatial competition, there are studies demonstrating how spatial competition is grounded in the neural system as Biased Competition describes it (Beck & Kastner, 2009; Desimone, 1998). All stimuli in the visual field compete to control behavior. They compete for neural representation that is for the neural response in visual cortex, by interacting in a mutually suppressing way. The closer the interacting neurons are located in the cortex the stronger their competition is. In terms of receptive fields, this implies that stimuli sharing a receptive field compete stronger than stimuli falling in different receptive fields. This spatial competition can be biased by stimulus properties or observer's goals. The theory of Biased Competition explains both, capture and non-capture events in the distractor search paradigm. If the target wins the competition, it is a non-capture trial, if the distractor wins the competition it is a capture trial. Because it accounts for both and, moreover, clearly describes the mechanism of competition, we consider it as qualified theory to explain our results.

Here, we simulated the predictions of competition models that predict non-capture or capture in the distractor search paradigm. These are plausible and well-established models of attentional selection in the literature that account for RT interference when a distractor is present. However, the leaky accumulator model (Usher & McClelland, 2001), that we used to simulate the predictions of the competition models, provides another possibility of how RT interference could emerge, namely by an increase of the non-decision time T_{er} when a distractor is present compared to absent. The simulated prediction about RT interference as a result of a varying non-decision time T_{er} is displayed in the Appendix (Figure A4). RT interference was equally distributed, i.e. it was the same for fast and slow RTs, which does not correspond to our experimental data. To our knowledge, there is no theoretical foundation for the influence of non-decision time on RT interference.

While a distractor induced interference on the one hand, it also facilitated target selection when this was very slow. This idea of facilitation due to a salient distractor was also reported by Geng and DiQuattro (2010), who presented their participants with two squared fields that were intersected by a “t-like” cross. One of the squares, with the horizontal bar in the middle, served as the distractor and the other, where the horizontal bar was located in the upper or lower half, served as target. The task was to manually indicate by button press whether the target had its horizontal bar in the upper or lower half. In the relevant experiment, salience in terms of luminance contrast of the squared fields was manipulated such that if a salient square was present, it always was the distractor, or target and distractor were equally salient. In a neutral condition there was only the target present. Eye movements were recorded and served as indicator for attentional capture by the distractor, although there was no explicit task for eye

movements. The findings were shorter RTs in capture trials (where the first saccade went to the distractor) when the distractor was more salient compared to when it was equally salient. The authors interpret this finding in the sense that top-down controlled rejection of the distractor is faster when it is salient. However, these authors compared only RTs for more salient and equal salient distractors and there is no report on the comparison between capture by a salient distractor and distractor absent RTs. This is exactly what is indicated by our finding of negative RT interference: a salient distractor speeds RT to the extent that is even faster than when there is no distractor present, not only when it is not salient. Geng and DiQuattro's (2010) explanation of top-down controlled fast rejection based on salience cannot account for our results, because in our experiments the salient object was not necessarily the distractor, but the role of the most salient object was unpredictable. Instead of rejecting the distractor based on salience, the most salient object had to be identified first and only then the second selection could be speeded. We suggest the second selection to be speeded, rather than a fast rejection of the distractor, because we found negative RT interference, which was predicted by the model that kept disengagement time constant, but accelerated the time of the second selection by lowering the selection threshold.

We used distribution analysis to distinguish attentional capture from slowing, i.e. non-capture, in the distractor search paradigm. Our results suggest attentional capture to occur, so much the more salient the distractor is compared to the target. Moreover, negative RT interference indicates faster RTs when the distractor is present compared to when a slowly selected target is presented alone. It seems that the second selection after attentional capture is accelerated to the time it takes to select the distractor and disengage from it. Therefore, we

conclude that RT interference in the distractor search paradigm is the result of spatial capture of attention rather than merely slowing due to filtering processes. The second target selection after attentional capture can be even be faster than on trials when there is only the target present.

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Figures

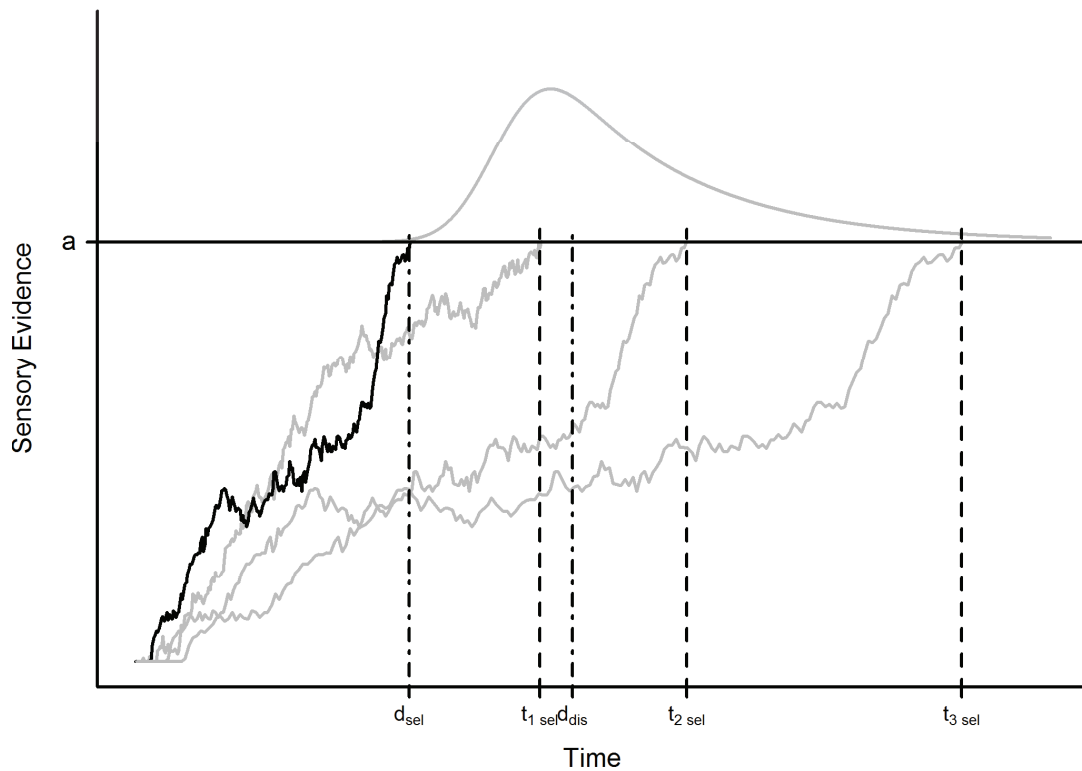


Figure 1. Target selection after attentional capture. One sample path of distractor selection is shown in black. Sample paths of different targets are shown in gray. The selection threshold a is set at the beginning of the trial. If target selection time exceeds distractor selection time d_{sel} plus disengagement time d_{dis} , as in case of target t_2 and t_3 , an immediate decrease of the selection threshold to the level of the next most salient stimulus is triggered. A target is then selected earlier than at its normal selection time t_{sel} . No such benefit occurs for target t_1 , because its normal selection time is earlier than the d_{dis} . The benefit is the more pronounced the longer target selection would take without a decrease of the threshold after attentional capture.

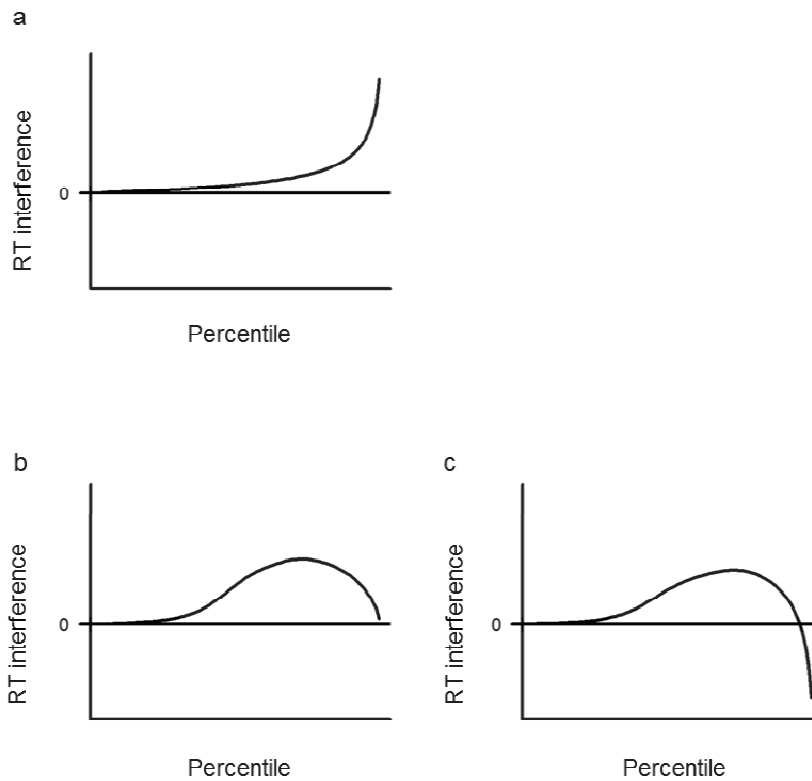


Figure 2. Predictions about the distribution of RT interference. Predictions were generated by leaky accumulator models with target and distractor represented by separate accumulator units. 100,000 simulated trials were run with the parameter estimates of target and distractor drift rate = 0.4, non-decision time $T_{er} = 200$ ms, its range $s_{er} = 0.01$ and threshold = 0.05. (a) Predictions of non-capture accounts. For distractor present trials, drift rate of the target was reduced to 0.16. (b) Predictions of a capture account with fixed threshold. Disengagement time was set to 140 ms. (c) Predictions of a capture account with a variable threshold for the second selection. Disengagement time was set to 140 ms, threshold was changed to the time of distractor selection plus disengagement time.

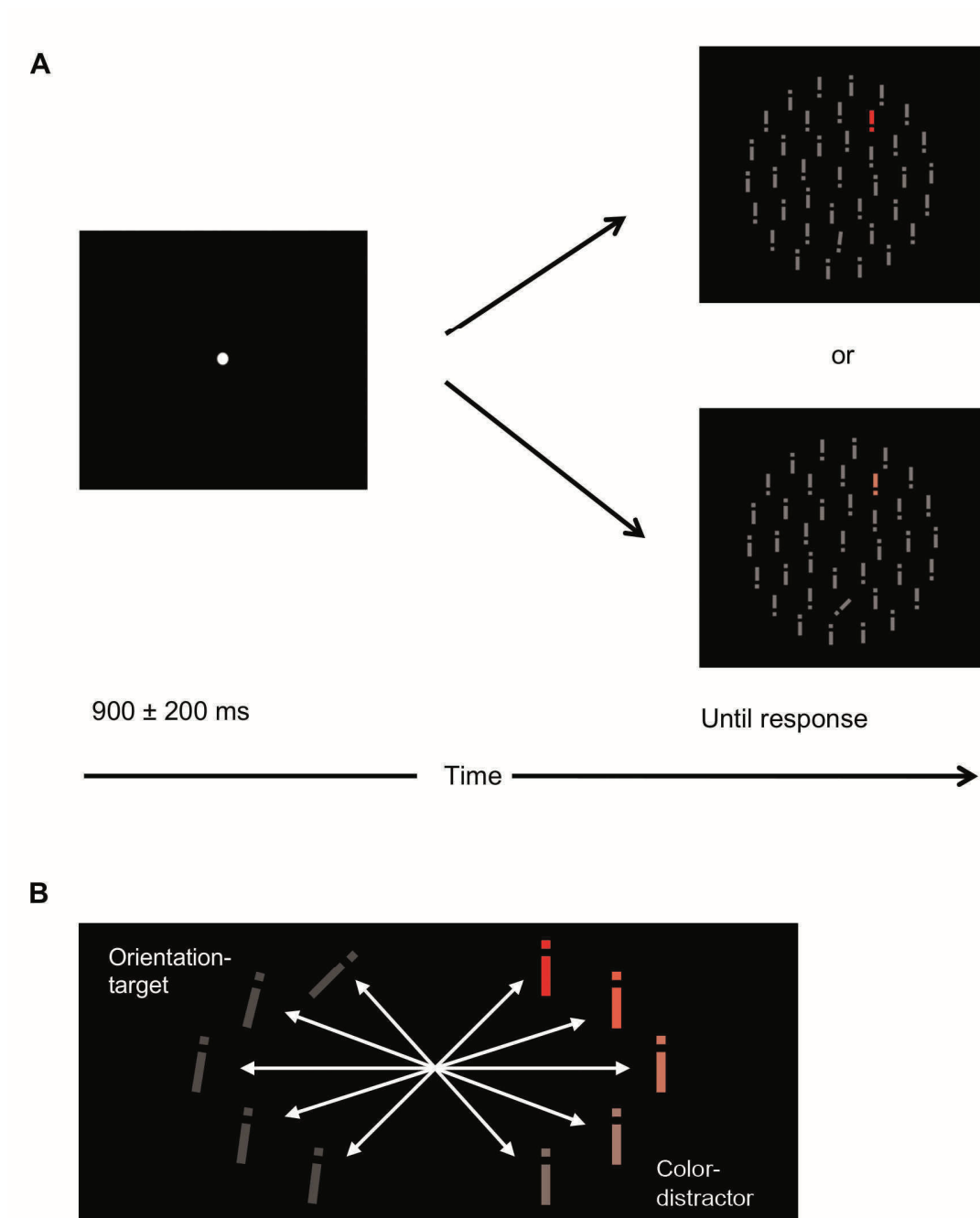


Figure 3. Experimental design and stimuli. (a) A search display, consisting of 39 broken grey bars arranged around three imaginary concentric circles, was presented in the center of the

screen, on a black background. There was always an orientation target; and in half of the trials (randomly determined), there was also a color distractor. Each trial started with a white fixation spot that was hidden while the display was presented until response. Inter-stimulus-intervals varied randomly in the range 900 ± 200 ms. While ignoring a color distractor, participants searched for a tilted target bar and decided, via a speeded button press, whether the gap was located at the top or the bottom of the bar. This response decision required focal attention to be allocated to the target. (b) 25 Saliency difference conditions resulted from 5 orientation and 5 color contrasts. Adapted figure from Zehetleitner et al. (2013).

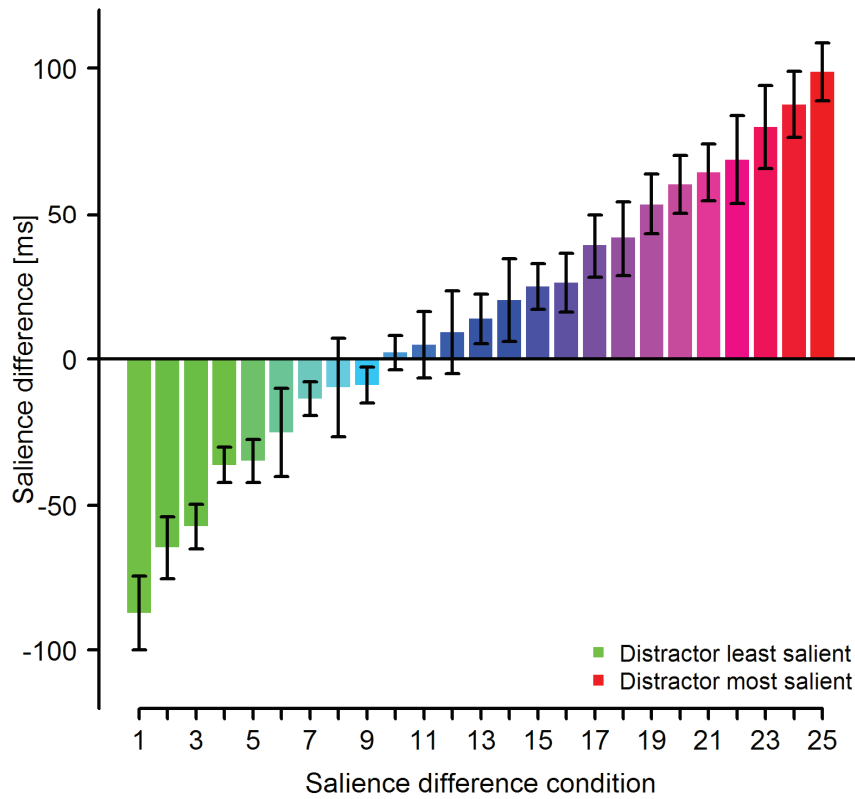


Figure 4. Relative salience between targets and distractors in experiment 1. Bars depict the mean difference between the detection times of orientation and color targets in the stimulus salience measurement, which served in the distractor experiment as targets and distractors, respectively. Error bars represent standard errors of the mean.

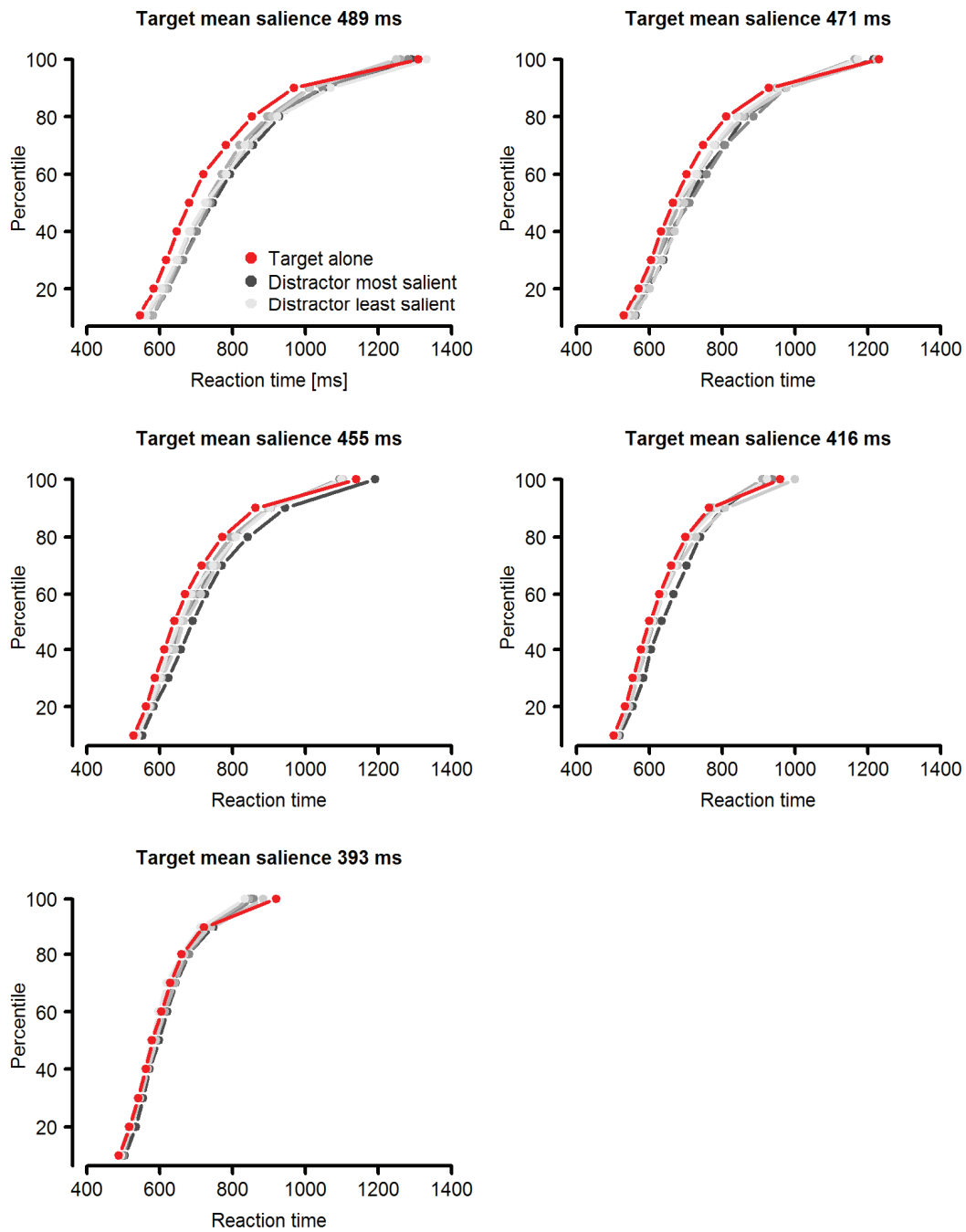


Figure 5. Cumulative distribution functions of all target distractor pairs in experiment 1.

Each panel represents CDF's of one target saliency and all distractor saliencies.

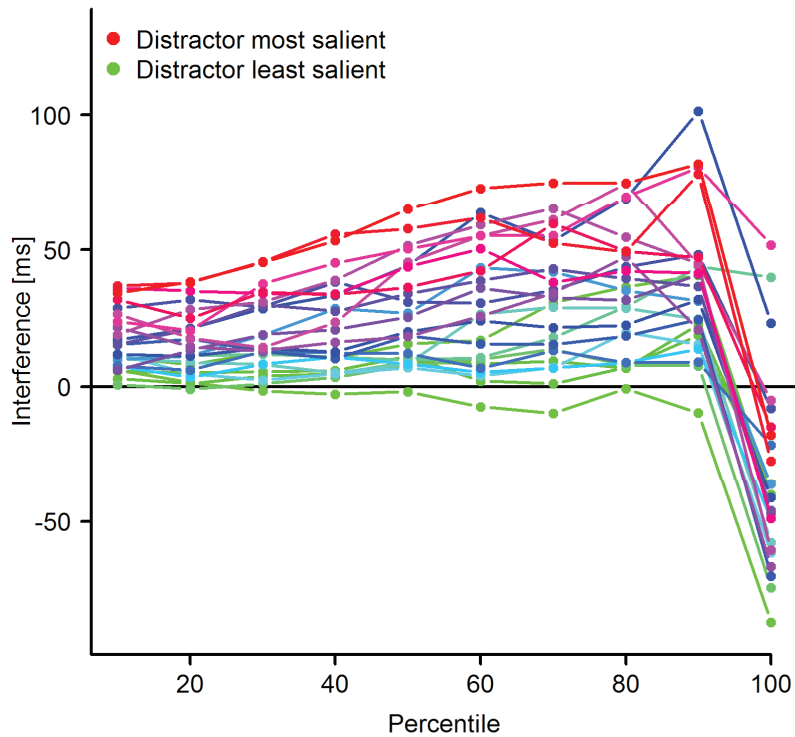


Figure 6. RT interference as a function of percentile in experiment 1. Each line represents the distribution of RT interference for a certain target-distractor-pair. Relative salience of each pair can be read out from Figure 4 with corresponding color code.

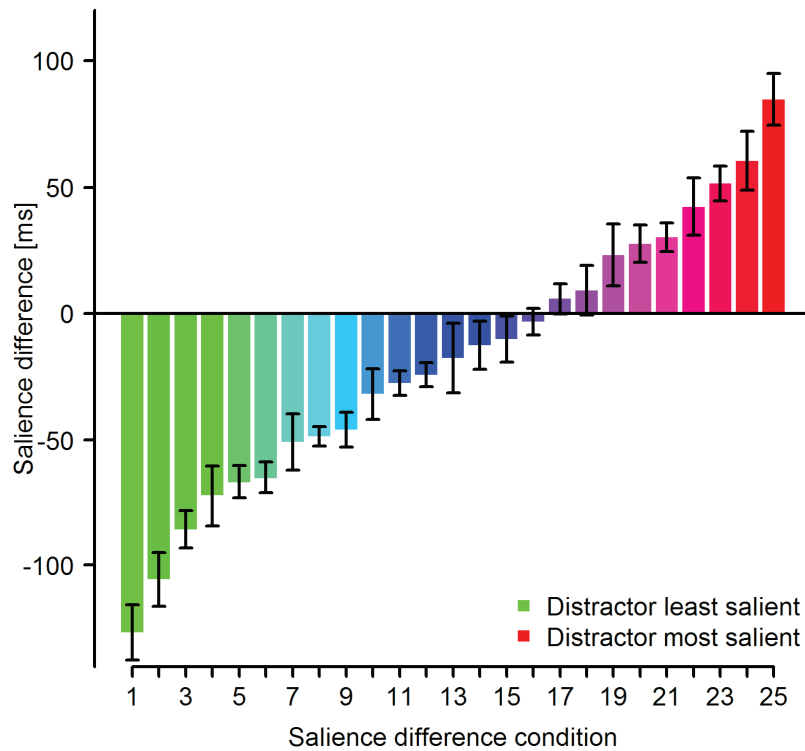


Figure 7. Relative saliency between targets and distractors in experiment 2. Bars depict the mean difference between the detection times of orientation and luminance targets in the stimulus saliency measurement, which served in the distractor experiment as targets and distractors, respectively. Error bars represent standard errors of the mean.

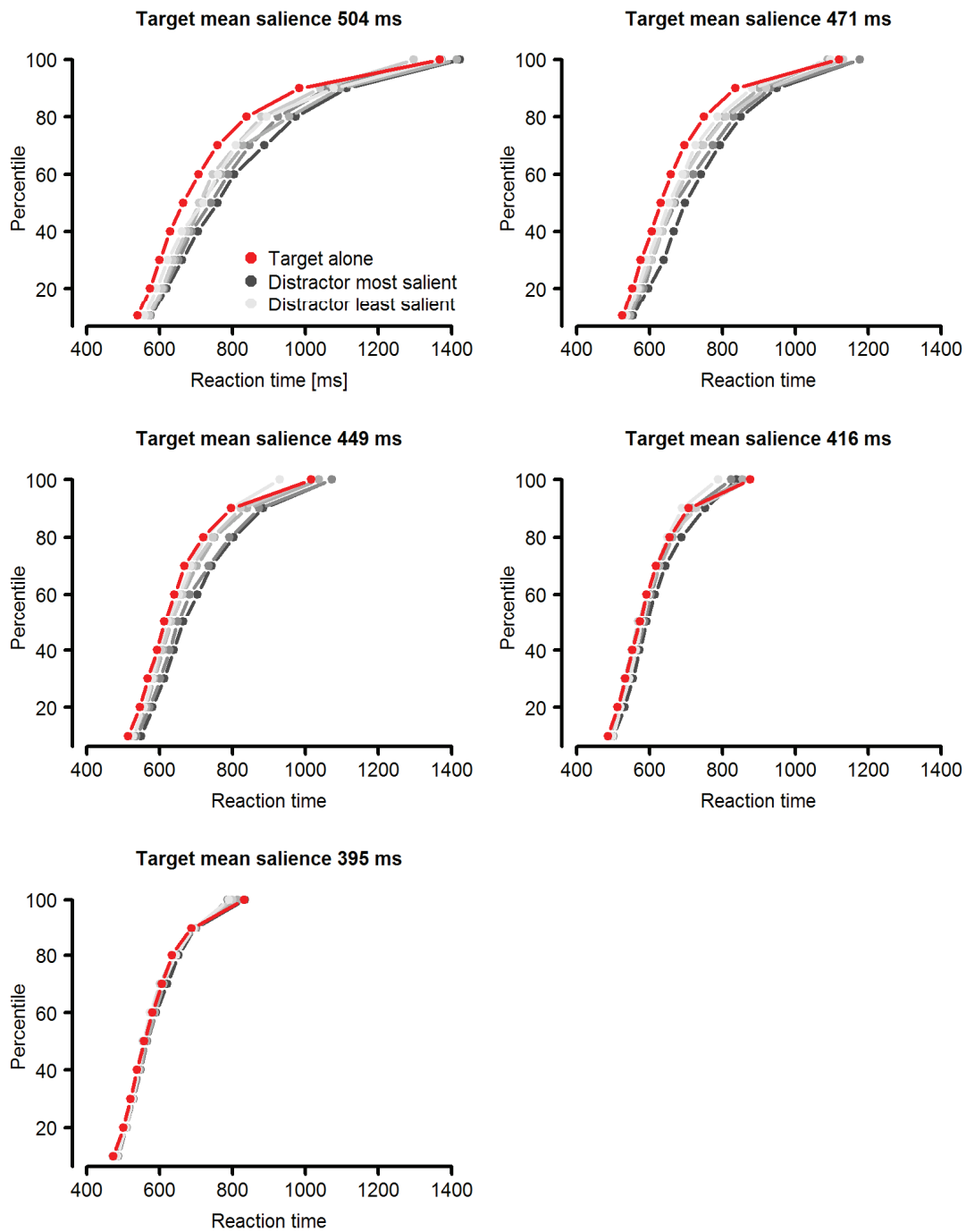


Figure 8. Cumulative distribution functions of all target distractor pairs in experiment 2.

Each panel represents CDF's of one target saliency and all distractor saliencies.

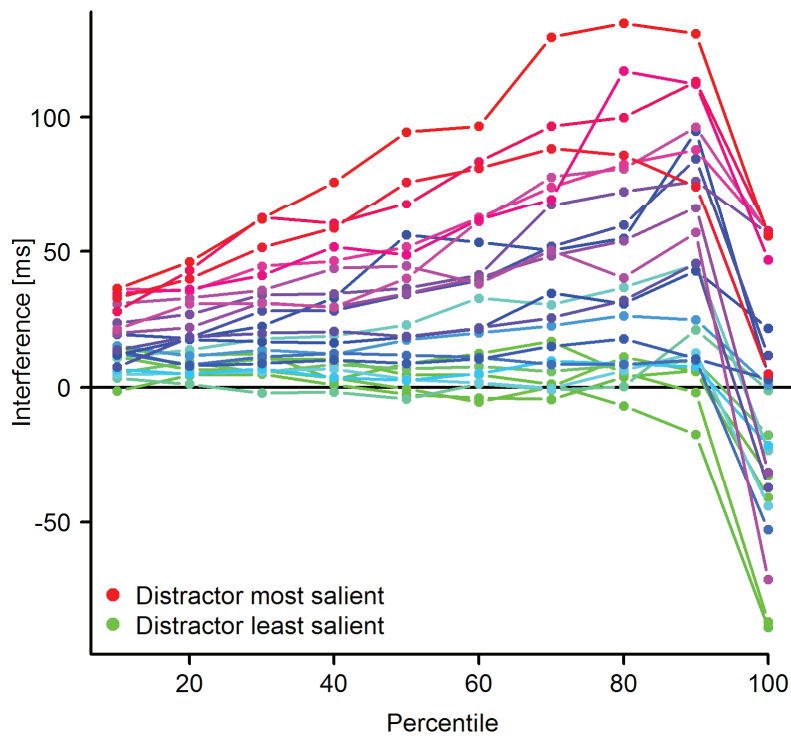


Figure 9. RT interference as a function of percentile in experiment 2. Each line represents the distribution of RT interference for a certain target-distractor-pair. Relative salience of each pair can be read out from Figure 7 with corresponding color code.

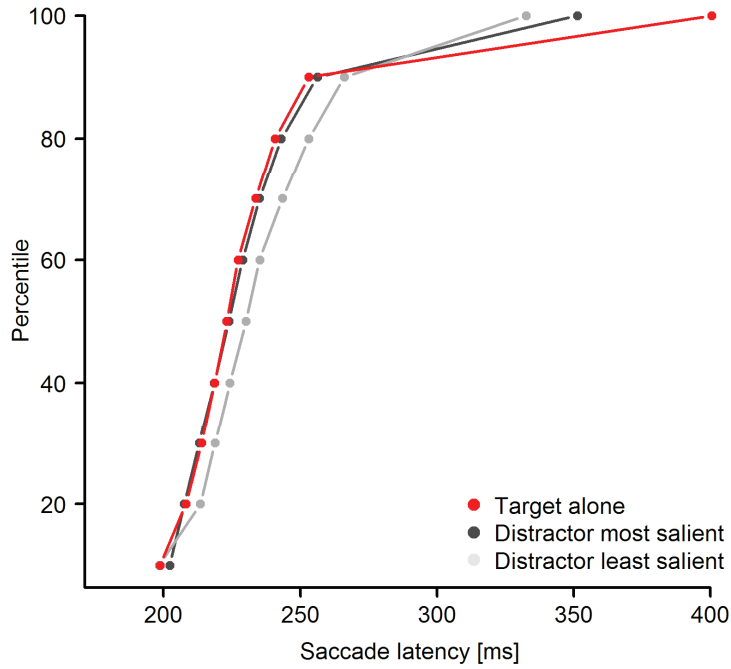


Figure 10. Cumulative distribution function of target distractor pairs in experiment 3.

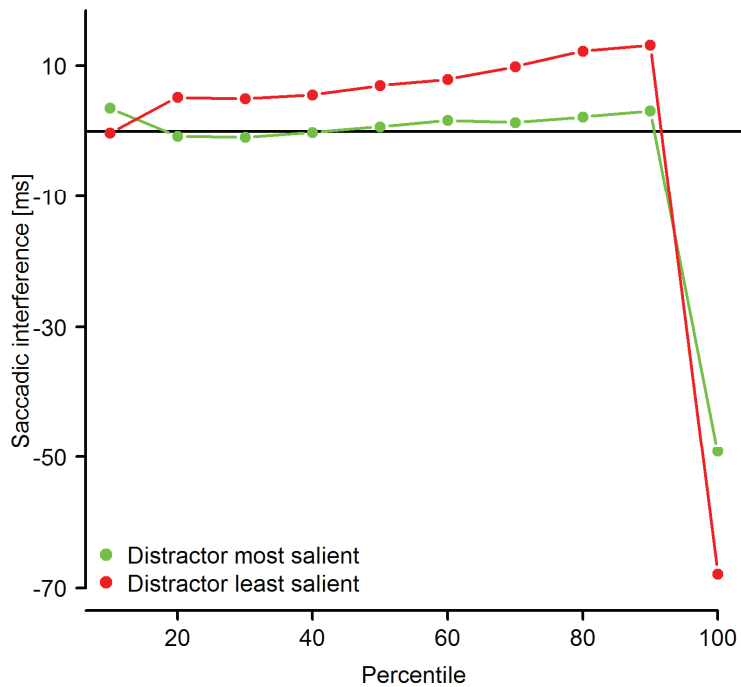


Figure 11. **Saccadic interference as a function of percentile in experiment 3.** Each line represents the distribution of saccadic interference for the distractor more and less salient than the target.

Appendix

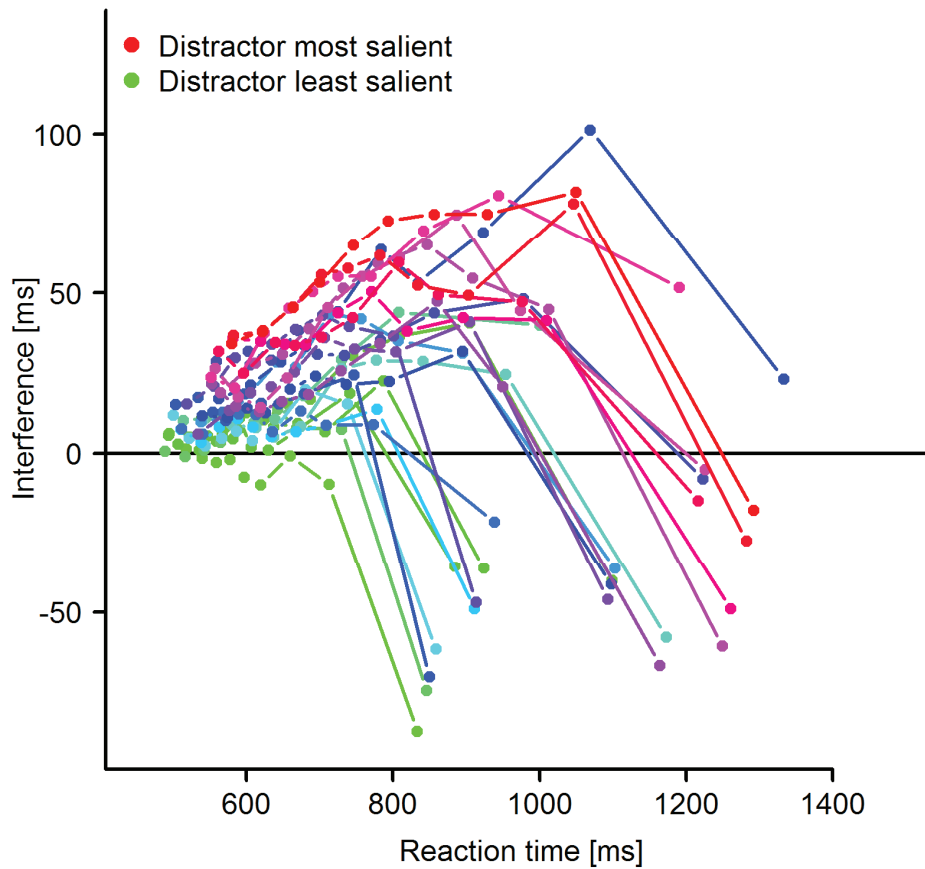


Figure A1. RT interference as a function of RT latency in experiment 1. Colors represent salience differences between target and distractor, corresponding to the color code of Figure 4.

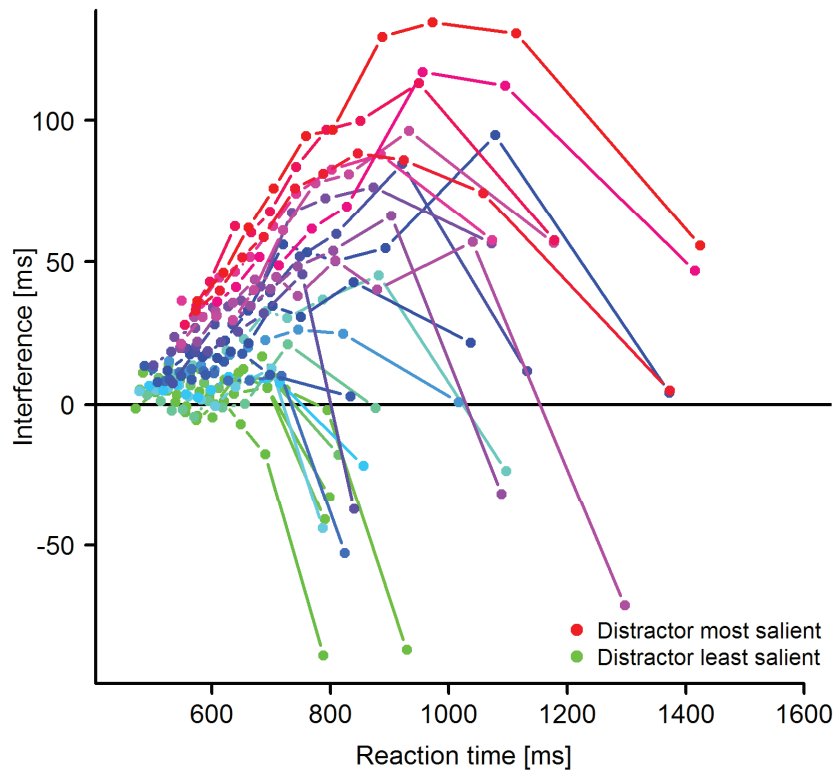


Figure A2. RT interference as a function of RT latency in experiment 2. Colors represent salience differences between target and distractor, corresponding to the color code of Figure 7.

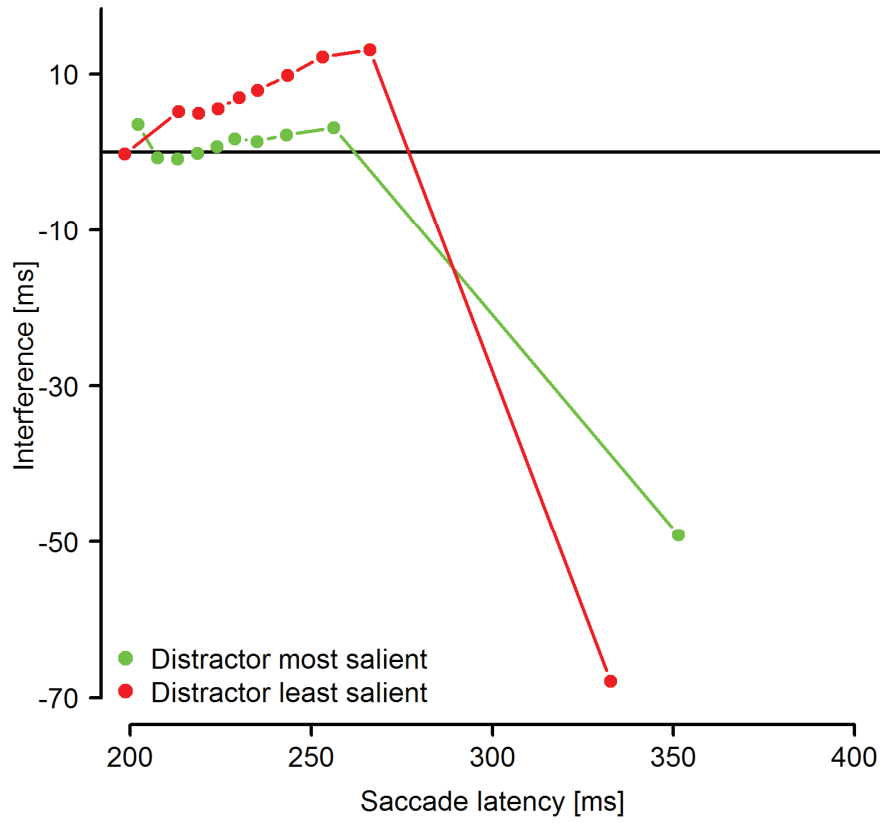


Figure A3. Saccadic interference as a function of saccadic latency in experiment 3.

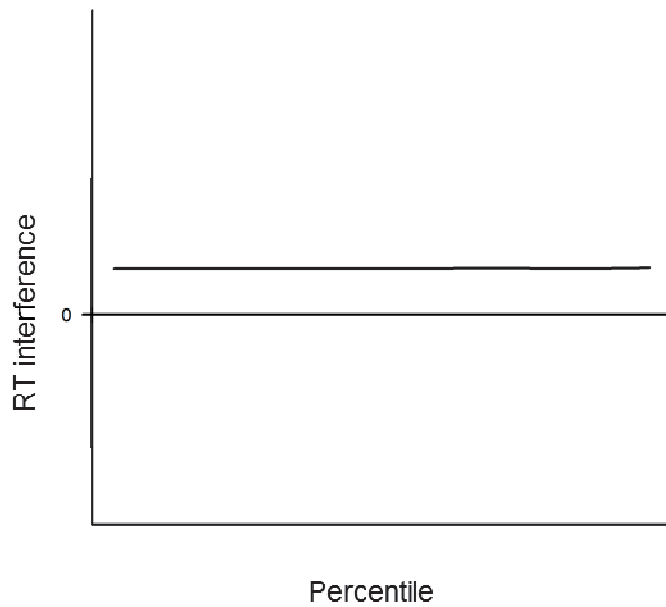


Figure A4. Predictions about the distribution of RT interference caused by a variable non-decision time T_{er} dependent on distractor presence. Predictions were generated by a leaky accumulator model with target and distractor represented by separate accumulator units. 100,000 simulated trials were run with the parameter estimates of target and distractor drift rate = 0.4, non-decision time T_{er} = 200 ms for target only trials and T_{er} = 2,200 ms for distractor present trials with a range s_{er} = 0.01 and threshold = 0.05. Disengagement time was set to 140 ms.

Eidesstattliche Erklärung

Hiermit versichere ich an Eides statt, dass ich die vorliegende Dissertation „A probabilistic theory of salience: Attentional selection and capture“ 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.

München, den 5. Juni 2013

A. Isabel Koch

Beiträge zu den einzelnen Publikationen

Zehetleitner, M.*, Koch, A. I.*, Goschy, H., & Müller, H. J. (2013). Saliency-based selection: Attentional capture by distractors less salient than the target. *PLoS ONE*, 8(1), e52595.

* Geteilte erste Autorenschaft: Beide Autoren haben gleichen Anteil am Entstehen der Publikation geleistet.

A.I.K. hat das Reaktionszeit- und Augenbewegungsexperiment zusammen mit M.Z. entwickelt und die Reaktionszeitdaten erhoben und analysiert. H.G. hat die Augenbewegungsdaten erhoben und analysiert. Die computationale Simulation wurde von M.Z. durchgeführt. A.I.K. hat zusammen mit M.Z. die probabilistische Salienztheorie entwickelt sowie die theoretischen Konsequenzen für die automatische Ausrichtung der Aufmerksamkeit abgeleitet. Schließlich hat A.I.K. das Manuskript zusammen mit M.Z. und H.J.M. geschrieben. Der Methodenteil des Augenbewegungsexperiments wurde zusammen mit H.G. geschrieben.

Koch, A. I., Müller, H. J., & Zehetleitner, M. (2013). Distractors less salient than targets capture attention instead of producing non-spatial filtering costs. *Acta Psychologica*, 144, 61-72.

A.I.K. hat die Experimente entwickelt, durchgeführt und die Daten analysiert. Außerdem hat A.I.K. das Manuskript zusammen mit M.Z. und H.J.M. geschrieben.

Koch, A. I., Goschy, H., Müller, H. J., & Zehetleitner, M. (2013). Distribution analysis of reaction time interference: Speeded target selection following attentional capture. Unpublished manuscript.

A.I.K. hat die Reaktionszeitexperimente entwickelt, die Daten erhoben und sie analysiert. H.G. hat das Augenbewegungsexperiment entwickelt und die Daten erhoben. A.I.K. hat die Daten des Augenbewegungsexperiments analysiert. Die computationalen Simulationen wurden von M.Z. durchgeführt. A.I.K. hat das Manuskript geschrieben.

Hiermit bestätigen die Autoren die angegebenen Beiträge zu den einzelnen Publikationen.

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Publikationen

Zehetleitner, M.*, Koch, A. I.*, Goschy, H., & Müller, H. J. (2013). Salience-based selection: Attentional capture by distractors less salient than the target. *PLoS ONE*, 8(1), e52595.

Koch, A. I., Müller, H. J., & Zehetleitner, M. (2013). Distractors less salient than targets capture attention instead of producing non-spatial filtering costs. *Acta Psychologica*, 144, 61-72.

Publikationen in Vorbereitung

Koch, A. I., Goschy, H., Müller, H. J., & Zehetleitner, M. (2013). Distribution analysis of reaction time interference: Speeded target selection after attentional capture. Unpublished manuscript.

Goschy, H., Koch, A. I., Müller, H. J., & Zehetleitner, M. (2013). Early top-down control over saccadic target selection: Evidence from a systematic salience difference manipulation. Unpublished manuscript.

Konferenzbeiträge

Koch, A. I., Müller, H. J., & Zehetleitner, M. (2012). Automatic attentional selection by low salient stimuli. 48. Kongress der Deutschen Gesellschaft für Psychologie. Bielefeld.

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