

# How priming in visual search affects response time distributions: Analyses with ex-Gaussian fits

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**Abstract** Although response times (RTs) are the dependent measure of choice in the majority of studies of visual attention, changes in RTs can be hard to interpret. First, they are inherently ambiguous, since they may reflect a change in the central tendency or skew (or both) of a distribution. Second, RT measures may lack sensitivity, since meaningful changes in RT patterns may not be picked up if they reflect two or more processes having opposing influences on mean RTs. Here we describe RT distributions for repetition priming in visual search, fitting ex-Gaussian functions to RT distributions. We focus here on feature and conjunction search tasks, since priming effects in these tasks are often thought to reflect similar mechanisms. As expected, both tasks resulted in strong priming effects when target and distractor identities repeated, but a large difference between feature and conjunction search was also seen, in that the  $\sigma$  parameter (reflecting the standard deviation of the Gaussian component) was far more affected by search repetition in conjunction than in feature search. Although caution should clearly be used when particular parameter estimates are matched to specific functions or processes, our results suggest that analyses of RT distributions can inform theoretical accounts of priming in visual search tasks, in this case showing quite different repetition effects for the two differing search types, suggesting that priming in the two paradigms partly reflects different mechanisms.

**Keywords** Attention · Priming · Visual Search · RT distributions · Ex-Gaussian function

A popular model of the function of visual attention is encapsulated in visual search tasks (Cavanagh & Chase, 1971; Neisser, 1964; Smith, 1962; Treisman, 1977). A key dependent variable used to assess the attentional requirements of a particular search task is how quickly and accurately observers find a predesignated target. The difficulty of search is typically assessed with mean response time (RT) and accuracy (Wolfe, 1998). But often, measures of central tendency and dispersion provide only limited information about the dynamics of the search process (Balota & Yap, 2011; Heathcote, Popiel, & Mewhort, 1991; Wolfe, Palmer, & Horowitz, 2010). For one thing, RT distributions are typically heavily skewed (Luce, 1986; McGill, 1963). This raises a potentially serious problem, since reporting only means and measures of dispersion carries the implicit assumption of a normal distribution. Such analyses are therefore ambiguous, since an increase in mean RT may reflect increased skew, a “lateral” shift in the distribution, or both. Additionally, meaningful changes in mean RT might even be obscured by opposing effects upon RT of two independent sources of variation (Balota & Yap, 2011).

Analyses of RT distributions have been performed for a number of tasks (see, e.g., Luce, 1986, as well as Antoniadou et al., 2013, and Balota & Yap, 2011, for recent discussions). Such analyses have not often been used on visual search data, however. But Wolfe et al. (2010) and Palmer, Horowitz, Torralba, and Wolfe (2011) showed how analyses of RT distributions might constrain theories of attentional selection in visual search arrays. Their results indicated, in fact, that many leading theories of visual search and attention cannot account for RT distributions from search tasks.

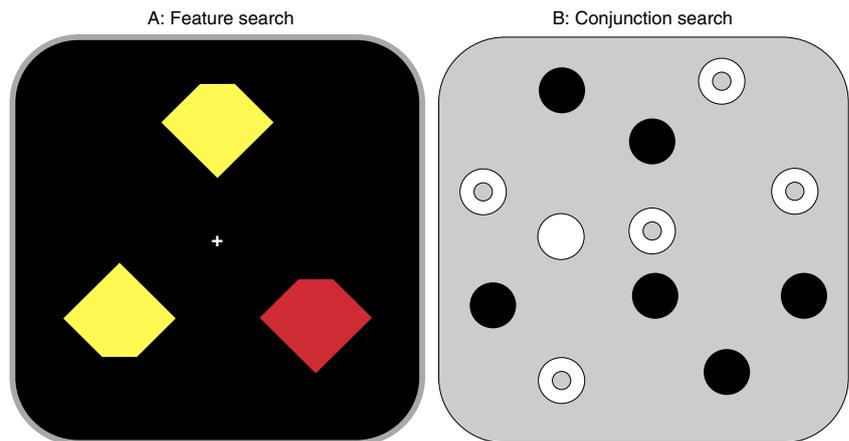
## Repetition priming in visual search

Repetition priming in visual search has a dominating influence on attentional orienting (Becker, 2008; Kristjánsson, Wang, &

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**Fig. 1** Sample experimental displays. Panel A shows the experimental display in the feature search, and panel B the experimental display in the conjunction search. Stimuli similar to the ones in panel B were used in Kristjánsson and Driver (2008)



Nakayama, 2002; Lamy, Bar-Anan, Egeth, & Carmel, 2006; Maljkovic & Nakayama, 1994), releasing visual stimuli from crowding (Kristjánsson, Heimisson, Róbertsson, & Whitney, 2013) and strongly determining attentional choice (Brascamp, Blake, & Kristjánsson, 2011; Chetverikov & Kristjánsson, 2014) and the affective evaluation of stimuli (Chetverikov & Kristjánsson, 2014). Priming may even account for large portions of effects that are often attributed to top-down guidance (Belopolsky, Schreij, & Theeuwes, 2010; Kristjánsson et al., 2002; Wang, Kristjánsson, & Nakayama, 2005; Wolfe, Butcher, Lee, & Hyle, 2003). Given the strength and prevalence of these priming effects, understanding them theoretically is vital for a thorough understanding of attentional selection.

Many accounts of priming have been proposed, ranging from feature facilitation views (Ásgeirsson, Kristjánsson, & Bundesen, 2014; Maljkovic & Nakayama, 1994), through episodic memory accounts (Huang, Holcombe, & Pashler, 2004; Thomson & Milliken, 2011) and accounts focused on the weighting of feature dimensions (Found & Müller, 1996), to response-priming accounts (Hillstrom, 2000). In a recent review, Kristjánsson and Campana (2010) concluded that priming is not a single, unitary phenomenon, but that it reflects modulations at various stages of processing, often depending on task demands. A number of recent findings have supported this view (Ásgeirsson & Kristjánsson, 2011; Kristjánsson, Saevarsson, & Driver, 2013; Rangelov, Müller, & Zehetleitner, 2013; Thomson & Milliken, 2011). Priming also varies by stimulus type (Campana, Pavan, & Casco, 2008) and is affected by interactions of stimulus features and position (Campana & Casco, 2009; Pratt & Castel, 2001).

The dependent measures most often used for between-trial priming in visual search are RTs and accuracy in search tasks presented until observers respond (Geyer, Müller, & Krummenacher, 2006; Kristjánsson, Ingvarsdóttir, & Teitsdóttir, 2008; Lamy et al., 2006; Maljkovic & Nakayama, 1994; Olivers & Humphreys, 2003). In other studies, accuracy in brief displays (Ásgeirsson et al., 2014;

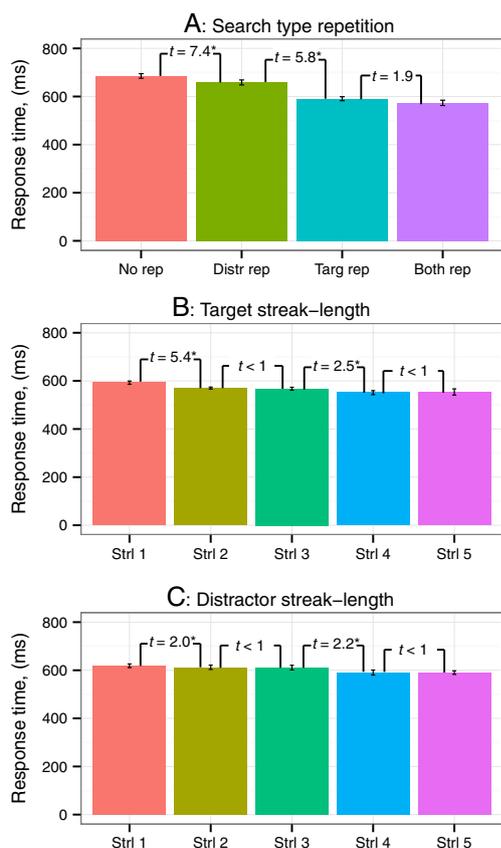
Lamy, Yashar, & Ruderman, 2010; Sigurdardóttir, Kristjánsson, & Driver, 2008) or the latency of the first saccade to a target (Becker, 2008; see also McPeck, Maljkovic, & Nakayama, 1999) are measured (see Lamy & Kristjánsson, 2013, for a review). This raises the possibility that crucial pieces of evidence may be ignored, since no distributional analyses of RTs exist for priming of visual search. Since distributions constrain attentional theories, they might also constrain theorizing about the effects of priming upon attentional selection.

### The present goals

Our aim here is to attempt to inform the literature on attentional priming by investigating RT distributions as they change with repetition priming. A key question that we address here is whether repetition effects are created equal in all visual searches. Priming is often assumed to reflect similar mechanisms, even when the tasks are very different (Hillstrom, 2000; Huang et al., 2004; see, e.g., Kristjánsson, 2008, for a review). We focus here on the priming of feature and conjunction search.

Priming might decrease the standard deviation, reflecting that priming decreases the number of extra-long RTs, and therefore the skew and variance of RT distributions. Priming might also induce a lateral shift simply affecting the mean of the distribution. Priming may also affect all estimated parameters. In fact, if Kristjánsson and Campana (2010) are indeed right that priming of visual search exerts its effects at various levels of perceptual processing, effects on all parameters might be expected, but we cannot assume that these effects would be comparable for both tasks. We address all of these points in what follows.

We tested two different visual search tasks: (1) A simple feature search, in which observers search for the



**Fig. 2** Response times (RTs) by experimental conditions in the feature search. Panel A shows the means of individual observers' RTs by repetition conditions. Panel B shows RTs by how often in a series of adjacent trials a particular target was repeated. Panel C shows performance as a function of how often in a series the distractor identity was repeated. The error bars represent  $2 \times$  within-subjects *SEMs*. All *t* values  $> 2$  are considered to represent significant differences (see the text)

odd-diamond-out among two distractor diamonds. This task involves a secondary discrimination task to assess focal attentional priming. We used the singleton-diamond task introduced by Bravo and Nakayama (1992) and used later by Maljkovic and Nakayama (1994) to introduce the priming of pop-out effect. (2) A conjunction odd-one-out task involving search for a singleton target that shares one feature with each of the two distractor sets, so that simple saliency through feature contrast cannot designate the target (Treisman & Gelade, 1980; Wolfe, 1998). The task was based on the one used by Wang, Kristjánsson, and Nakayama (2005) and Kristjánsson and Driver (2008). Priming of visual search has been observed for both of these paradigms. Finally, we analyzed a preexisting data set (Kristjánsson & Driver, 2008) in which conjunction and feature searches were contrasted within blocks in the same task, for a more direct comparison of the two searches than the preceding searches allowed.

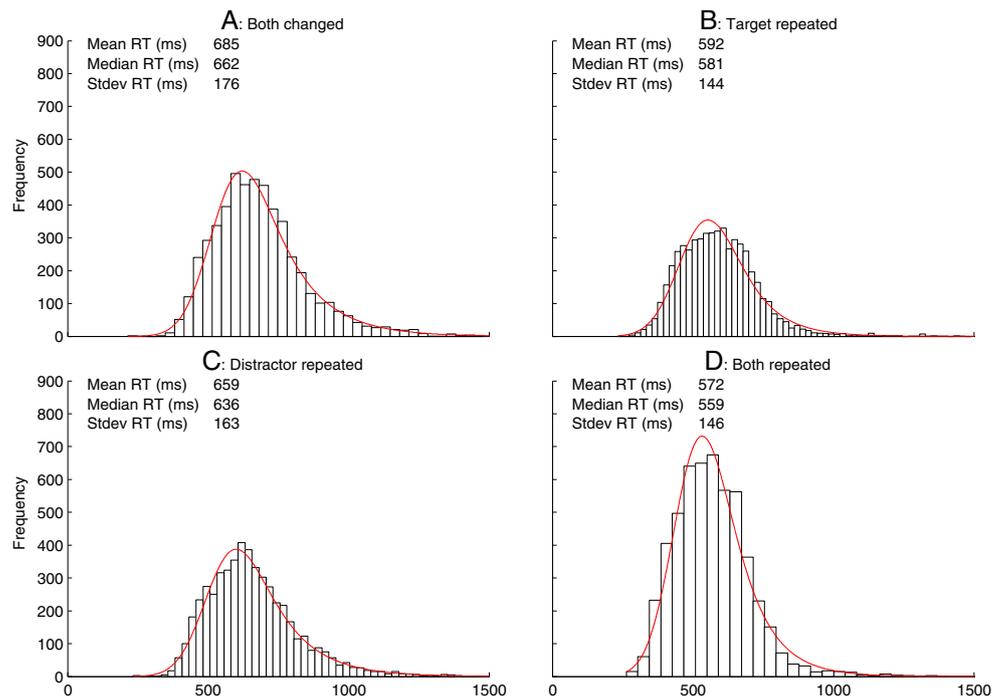
## Fitting procedure

We fitted an ex-Gaussian distribution to the RTs. Palmer et al. (2011) fitted visual search RT data to four different functions, with the ex-Gaussian showing marginally the best fits. The ex-Gaussian is a convolution of a Gaussian and an exponential distribution (Burbeck & Luce, 1982; Dawson, 1988; Hockley, 1984; Ratcliff, 1979). The  $\mu$  parameter represents the mean of the Gaussian, and  $\sigma$  its standard deviation. The  $\tau$  parameter corresponds to the mean and variance of the exponential distribution. The mean of the ex-Gaussian can therefore be defined as  $\mu + \tau$ , and its variance by  $\sigma^2 + \tau^2$  (Burnham, 2013; Luce, 1986; Yap, Balota, Cortese, & Watson, 2006).

The ex-Gaussian has a longer tail on the right than the left, therefore fitting RT distributions well (Dawson, 1988; Hockley, 1984; Hohle, 1965; Ratcliff, 1979; Ratcliff & Murdock 1976). Heathcote et al. (1991) argued that ex-Gaussian fits are essentially theory-neutral but can provide very useful three-parameter summaries of RT data. Nevertheless, attempts have been made to relate the particular parameters to specific cognitive mechanisms (Burnham, 2013; Dawson, 1988; Hohle, 1965; McGill, 1963; McGill & Gibbon, 1965). For example, Hockley (1984) argued that  $\tau$  reflected motor or neural delays, whereas Palmer et al. (2011) suggested that  $\tau$  may reflect set-size effects in conjunction search. Attempts at such characterizations have not yielded consistent results, however. Spieler, Balota, and Faust (2000) cautioned against precise matching of parameters and cognitive processes, concluding that “fitting functions . . . provides important insights by revealing regularities in the structure of the empirical data that in turn can guide and constrain theories of underlying cognitive processes” (p. 508). Matzke and Wagenmakers (2009) similarly cautioned against relating changes in particular parameter values to changes in specific cognitive components, while at the same highly encouraging the use of the functions for describing RT data and constraining theoretical accounts. The main usefulness of the ex-Gaussian function in terms of analyses may therefore be its summarizing virtues for tasks in which decisions must be made between two response alternatives, as is the case here (Heathcote et al., 1991; Matzke & Wagenmakers, 2009).

Our hope was that fitting the ex-Gaussian might provide a way of describing how particular experimental manipulations, such as the repetition of different visual search types, influence RT distributions. We agree with Spieler et al. (2000) and Matzke and Wagenmakers (2009) that this method has provided valuable information regarding selective-attention tasks. But it is important to note that fitting an ex-Gaussian does not entail any

**Fig. 3** Response time (RT) density plots and histograms for repetition conditions in the feature search, averaged over condition, (A) when neither target nor distractors repeated, (B) when the target repeated, (C) when the distractors repeated, and (D) when both target and distractors repeated. The curves are ex-Gaussian fitted curves, and the bars are histograms of the RTs. The bin widths are 20 to 40 ms



assumption on our part that RT distributions do, in fact, have a Gaussian and an exponential component.

We are aware that others might argue that other methods are more appropriate, such as the diffusion model (Ratcliff, 1978) or the ex-Wald distribution (a convolution of an exponential and a Wald, 1947, distribution). Some have argued that these two methods have clearer interpretations of parameters in terms of cognitive processes, but there is no consensus on this (Matzke & Wagenmakers, 2009), and it is beyond the scope of the present study to make strong claims in this regard. We will make the data set that we use here available to those who may wish to test other models of RT distributions as a function of priming.

## Method

### Participants

Seven volunteers from the University of Iceland (26–37 years of age; four male, three female) participated. Since optimal curve fitting requires a large number of trials, all but one observer participated in 3,200 trials (that one took part in 1,900 trials) in the feature search task, whereas four of the observers (26–37 years old; two male, two female) participated in 4,800 trials<sup>1</sup> each

<sup>1</sup> For one observer, the target was present on 79 % of trials. This did not affect the pattern in his data relative to the other observers (see, e.g., Fig. 9 below).

in the conjunction search. Their visual acuity was normal or corrected to normal.

### Equipment

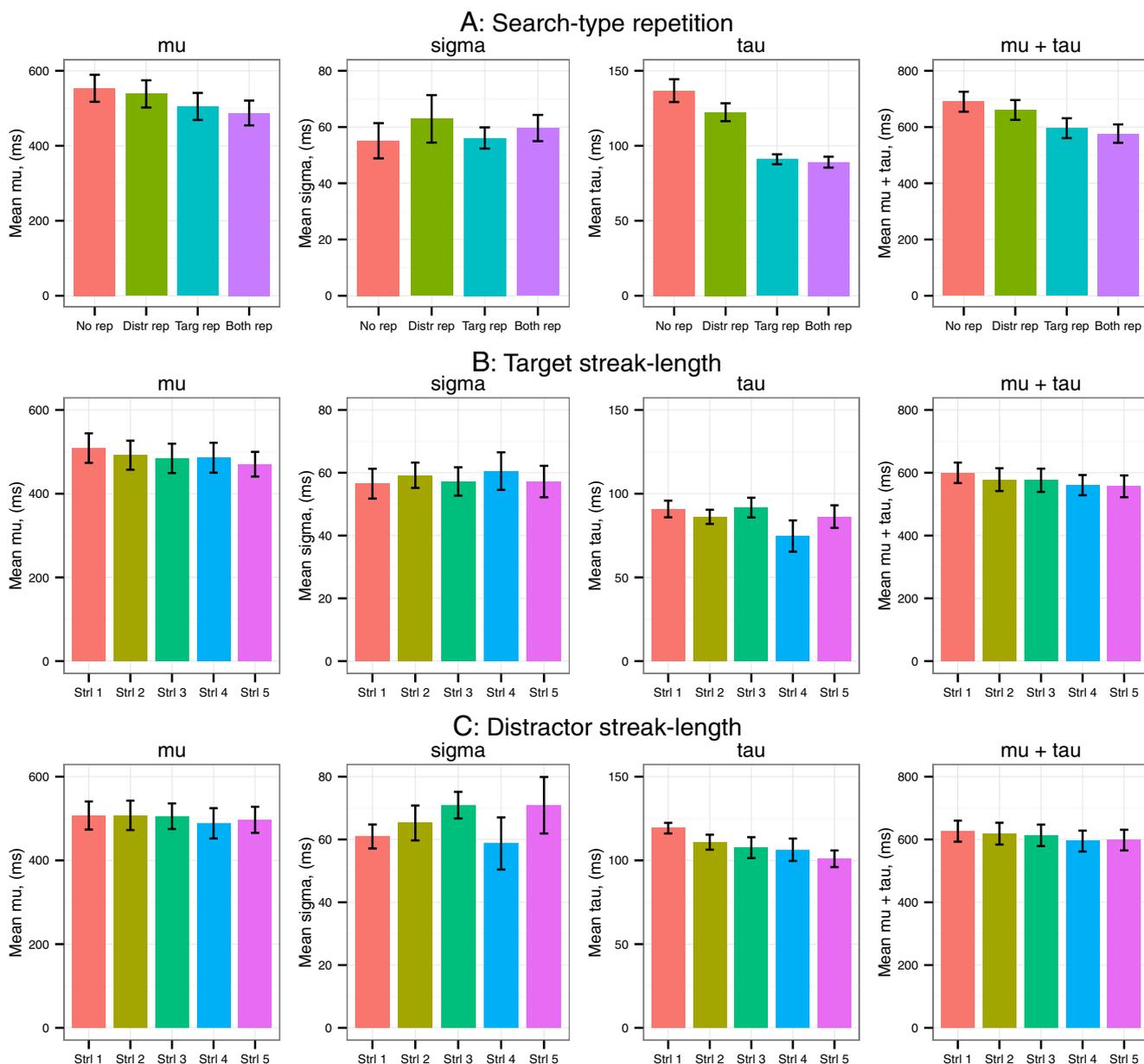
The experimental displays were programmed in C using the VisionShell software library and presented on a 75-Hz CRT controlled by a 400-MHz G4 Apple computer.

### Stimuli and procedure

Each trial in both tasks started with the presentation of a central white ( $56.6 \text{ cd m}^{-2}$ ) fixation cross. Following a variable interval (1,000–1,500 ms, randomly determined for each trial), the experimental stimuli appeared. Auditory feedback was provided on whether the answer was correct or incorrect. The viewing distance was 60 cm.

### Feature search task

The task was to locate the oddly colored diamond among two distractor diamonds (so the target was, e.g., the red diamond among yellow distractors; all diamonds were of the same size:  $2.4^\circ$  by  $2.4^\circ$ ; see Fig. 1A), judging by keypress whether there was a small notch at the top or the bottom of the target (all stimuli had such notches). On different blocks, the target color varied between red ( $22.7 \text{ cd m}^{-2}$ ) and green ( $27.6 \text{ cd m}^{-2}$ ), and the distractor color varied independently between yellow ( $37.4 \text{ cd m}^{-2}$ ) and blue ( $24.6 \text{ cd m}^{-2}$ ). Therefore, no intertrial role reversals between target and distractors were possible. On



**Fig. 4** Average ex-Gaussian parameter values for different repetition types, streaks of repeated targets, and streaks of repeated distractors. Error bars represent 1× between-subjects SEMs

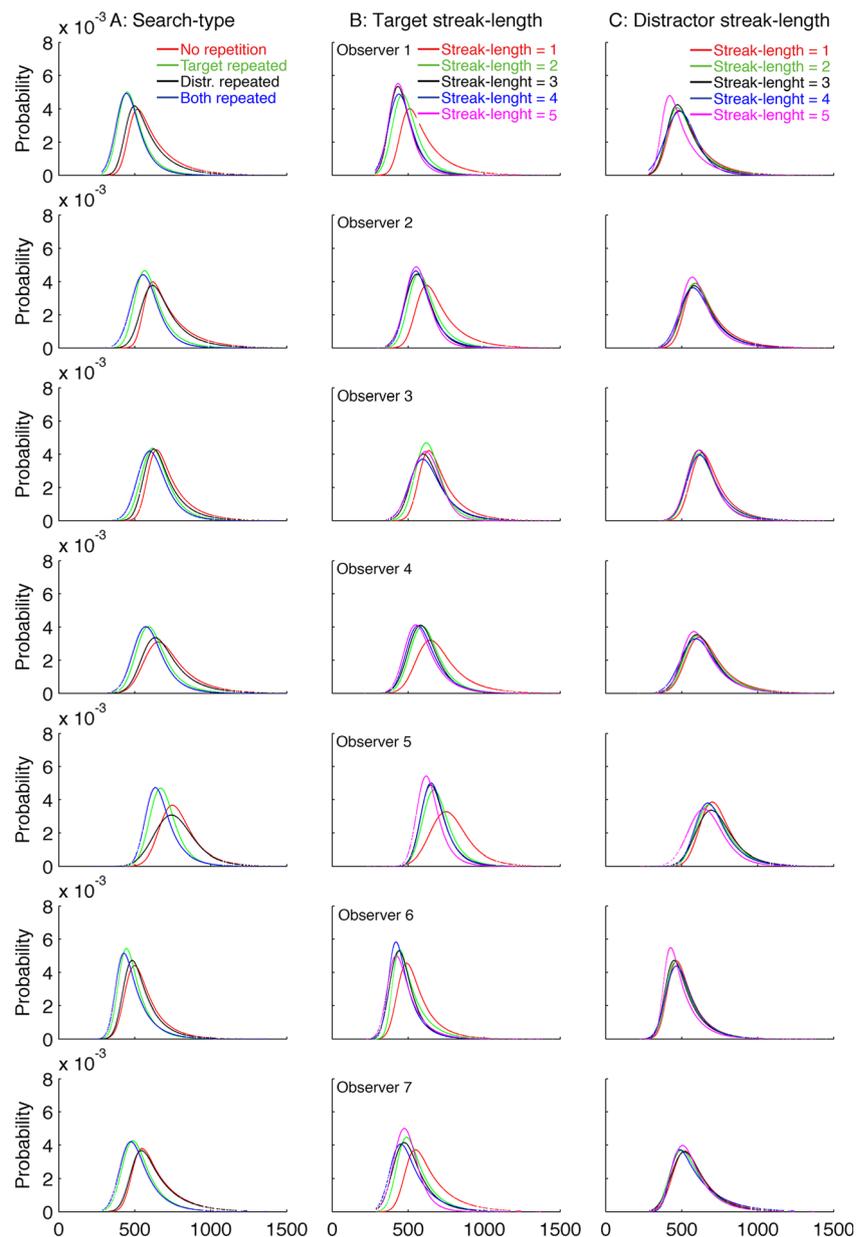
the other half of the blocks, the color scheme of the target and distractors was reversed. The diamonds were equally spaced (120° between them) on an imaginary circle with a radius of 4.8° and appeared on a dark gray (5.6 cd m<sup>-2</sup>) background.

**Conjunction search task**

The task was to determine by keypress whether an odd-one-out target was present or absent. There were six possible search types, with four types of target-present trials: black (0.8 cd m<sup>-2</sup>) square target among white (56.6 cd m<sup>-2</sup>) squares and black disks, white square target among black squares and white disks, white disk target among black disks and white

squares, and black disk target among white disks and black squares (see Fig. 1B). Since our aim was, at this point, not to investigate priming effects between adjacent target-absent trials, the target was present on 70 % of trials. Two possible types of no-target trials were created: white disks and black squares and black disks and white squares. The disks had a diameter of 1.1°, whereas the side length of the squares was 0.9°. Set size was either 14 or 28, determined randomly for each trial. The items were equally distributed on an invisible 8×8 grid (cell size=2.2°) with a slight random position jitter (±0.4°) within each cell to introduce irregularity. The search items in the conjunction search appeared on an approximately mid-gray background (33 cd m<sup>-2</sup>).

**Fig. 5** Ex-Gaussian fits for each observer as a function of search type and repetition (A), target streak length (B), and distractor streak length (C)



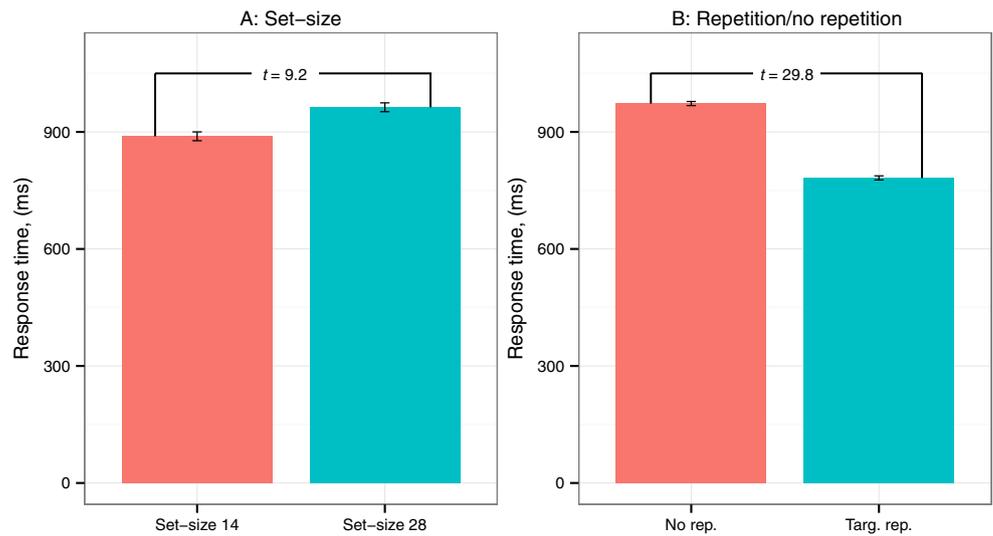
### Data analysis

We followed the example of Wolfe et al. (2010) and Palmer et al. (2011) by excluding trials with RTs longer than 4,000 ms in the feature search and longer than 8,000 ms in the conjunction search, and RTs shorter than 200 ms in both tasks (39 trials removed). We used the `lmer` (linear mixed model; Bates, 2010) function in R to test for significant effects of the experimental conditions on RTs in the unfitted data. The `lmer` function, however, does not provide  $p$  values, and we therefore report the  $t$  values, where  $t$  values  $>2$  are considered to represent significant differences (see, e.g., Baayen, Davidson, & Bates, 2008). We used the

`plotefit.m2` function to plot the density and histograms plots (Figs. 3 and 7), and the `egfit.m` function (Lacouture & Cousineau, 2008) in MATLAB to estimate the three ex-Gaussian parameters: the  $\mu$  and  $\sigma$  parameters denoting the mean and standard deviation of the Gaussian, and  $\tau$  the mean of the exponential part (Matzke & Wagenmakers, 2009; Ratcliff, 1993). To check for significant effects of condition on the ex-Gaussian parameters, we used repeated measures analyses of variance (ANOVAs). Error bars denote twice the within-subjects standard error, following the

<sup>2</sup> The number of bins was always 75, and the range of the bin widths is reported in each figure.

**Fig. 6** Response times by experimental conditions for the conjunction search task. Error bars represent 2× within-subjects SEMs, and *t* values >2 are considered to represent significant differences



method used by Kliegl, Wei, Dambacher, Yan, and Zhou (2010), in Figs. 2 and 6; otherwise, they denote 1× between-subjects SEMs.

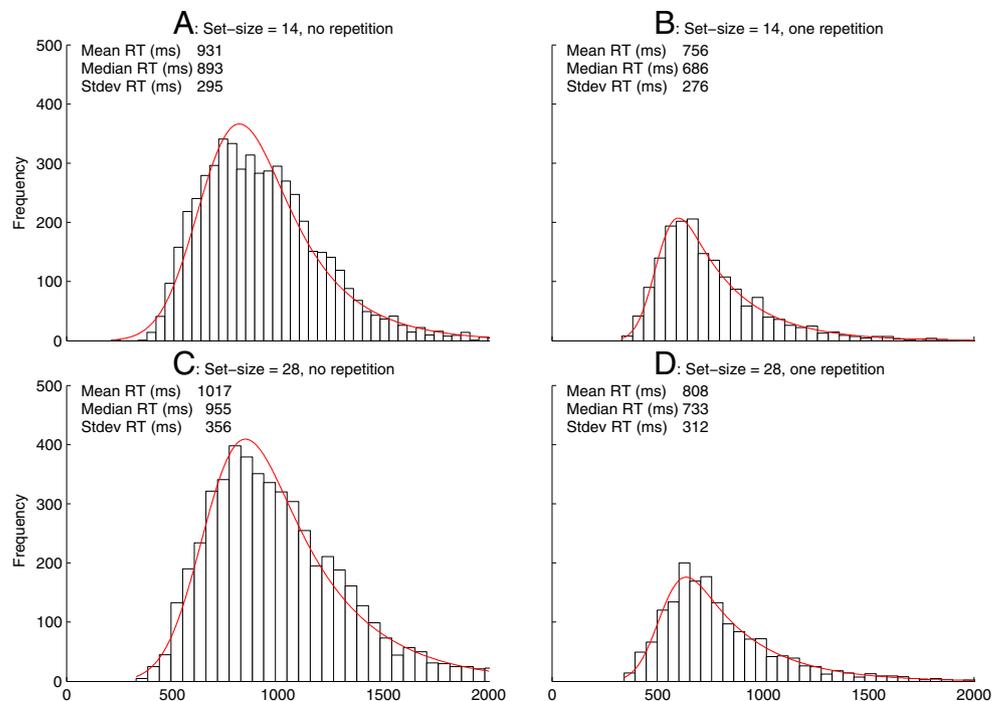
**Results**

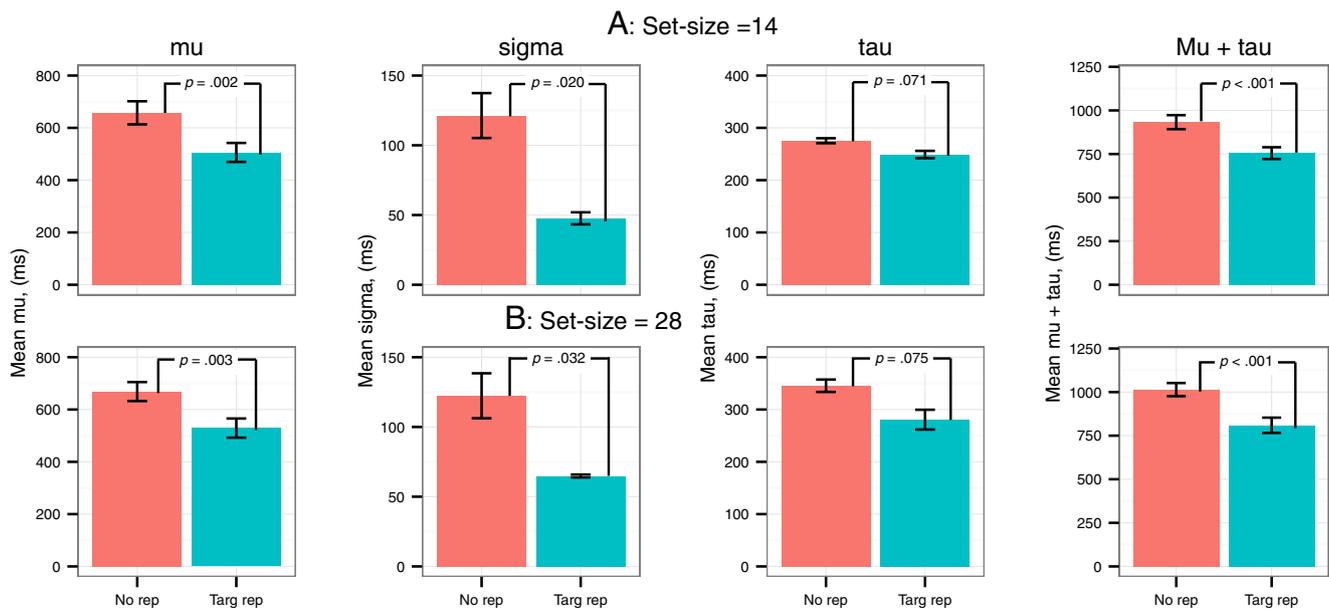
Feature search task

Overall performance was assessed with linear mixed modeling using sliding contrasts (Kliegl et al., 2010) to compare adjacent levels of whether the target, distractors, or both were repeated, and how often the

target and distractors repeated. We always present the absolute *t* values. The RTs were longest when neither the target nor distractors repeated, with a smaller speed benefit of distractor than of target repetition, and the shortest RTs when both the target and distractors were repeated (Fig. 2A). When the target was repeated one to five or more times, RTs decreased steadily (Fig. 2B), and the pattern for distractors was the same (Fig. 2C). Comparisons between the conditions and test results are shown in Fig. 2. The different panels contrast the repetition effects by (A) repetition type, (B) target streak length (how often in a row the same target was presented), and (C) distractor streak length (how often in a row

**Fig. 7** Response time (RT) density plots and histograms for the different repetition conditions, along with means, medians, and standard deviations averaged over observers. The curves are ex-Gaussian-fitted curves, whereas the bars are histograms of the RTs. The bin widths are 42 to 54 ms





**Fig. 8** Average ex-Gaussian parameter values for conjunction search, as a function of whether or not search was repeated. Error bars represent  $1 \times$  between-subjects SEMs

the same distractors were presented). The basic RT analyses show that our feature task generates strong priming patterns, reminiscent of what has been seen before in the literature, indicating that this task lends itself well to the analyses that we undertook here. Error rates ranged from 2.2 % to 7.1 % for the different observers.

**Ex-Gaussian fit** Figure 3 shows the RT histograms for the four different repetition conditions (target, distractor, both, or neither repeated), along with the ex-Gaussian fits and the means, medians, and standard deviations. The average ex-Gaussian parameters are shown in Fig. 4. A repeated measures ANOVA was used to compare the effects of the experimental conditions on the ex-Gaussian parameters. The main effect of repetition condition (Fig. 4A) on  $\mu$  was significant [ $F(3, 18) = 77.7, p < .001$ ]. The effect of repetition condition on  $\tau$  was also significant [ $F(3, 18) = 33.1, p < .001$ ], as was its effect on the combination of  $\mu + \tau$  [ $F(3, 18) = 113.1, p < .001$ ]. The effect of repetition condition on  $\sigma$ , on the other hand, was far from significant ( $F < 1$ ).

We next turn to the cumulative effects of target repetition, on the one hand, and distractor repetition, on the other (Fig. 4B). The main effect of target streak length on  $\mu$  was significant [ $F(4, 24) = 5.4, p = .003$ ] but not the effect on  $\sigma$  ( $F < 1$ ), and the effect on  $\tau$  was only marginal [ $F(4, 24) = 2.3, p = .09$ ], although there was an undeniable trend in the data in the second case. Finally, the main effect of target streak length on  $\mu + \tau$  was significant [ $F(4, 24) = 16.2, p < .001$ ]. The main effects of distractor streak length (Fig. 4C) on  $\mu$  and  $\mu + \tau$  were significant [ $F(4, 24) = 2.8, p = .049$ , and  $F(4, 24) = 13.7,$

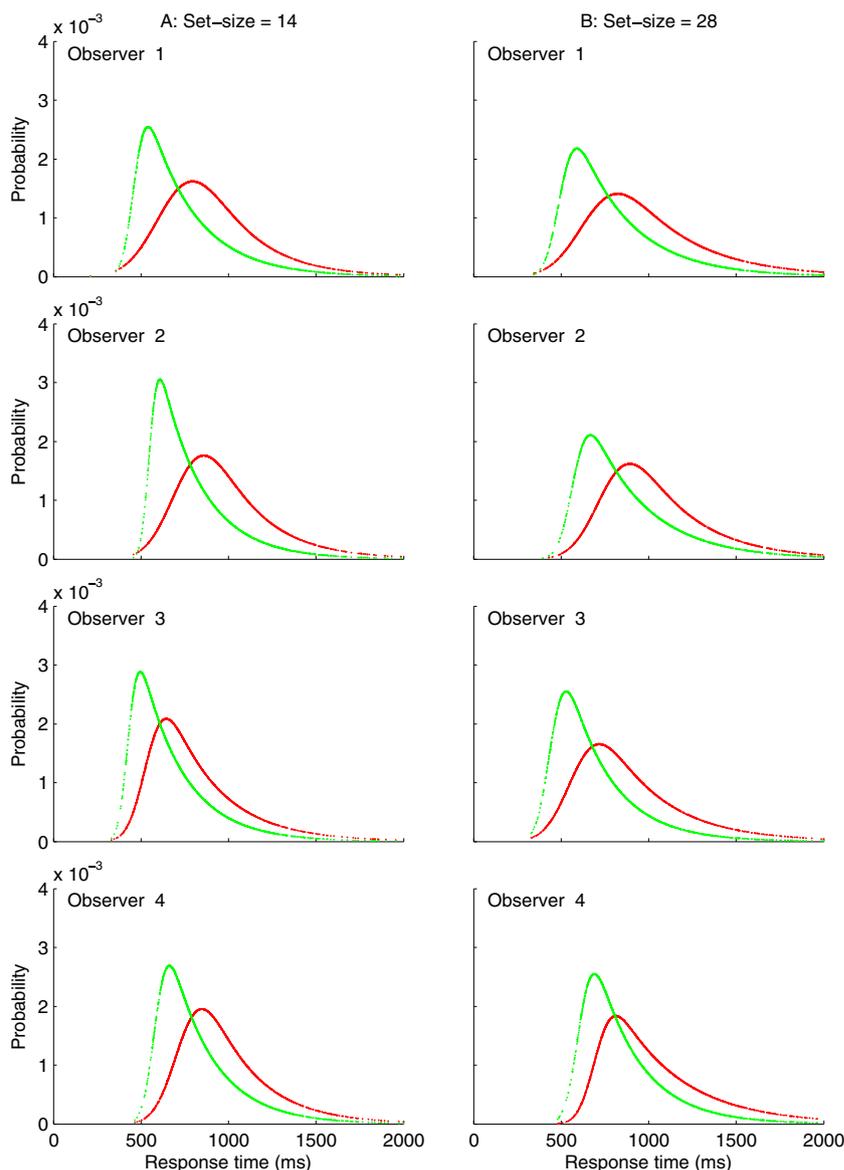
$p < .001$ , respectively], but not on either  $\sigma$  [ $F(4, 24) < 1, p = .43$ ] or  $\tau$  [ $F(4, 24) = 1.3, p = .3$ ]. Figure 5 shows the ex-Gaussian fits for the seven individual observers, as a function of repetition condition in column A, of target streak length in column B, and of distractor streak length in column C.

**Discussion: Feature search task** Repetition of targets or distractors in the feature search task mainly influenced the  $\mu$  and  $\tau$  parameters of the fitted ex-Gaussian distributions, but not the  $\sigma$  parameter. As we discussed before, the mean of the Gaussian distribution is represented by  $\mu$ , whereas  $\tau$  represents the mean of the exponential part, so in feature search the repetition conditions appear to have their largest effect on the means, whereas the variance appears not to be affected. This may indicate that repetition induces an overall speeding effect upon feature search, rather than a decrease in the number of trials with very long RTs.

It is also of interest that target and distractor repetition seem to have their own independent effects, which appear to be additive (consistent with the claims of Geyer et al. 2006; Kristjánsson & Driver 2005, 2008; Lamy, Antebi, Aviani, & Carmel, 2008; Saevarsson, Jóelsdóttir, Hjaltason, & Kristjánsson, 2008). Note, however, that the effects on the parameters of distractor repetition were smaller, in line with the smaller overall effect of distractor repetition in this paradigm.

We reiterate that caution should be used when individual parameters are interpreted, but the lack of any effect on  $\sigma$ , which represents the standard deviation of the Gaussian component, is quite notable, suggesting

**Fig. 9** Ex-Gaussian fits as a function of repetition in conjunction search for individual observers. Warmer lines present no repetition, and the cooler lines search repetition



that target repetition in feature search does not modulate the variance in responses.

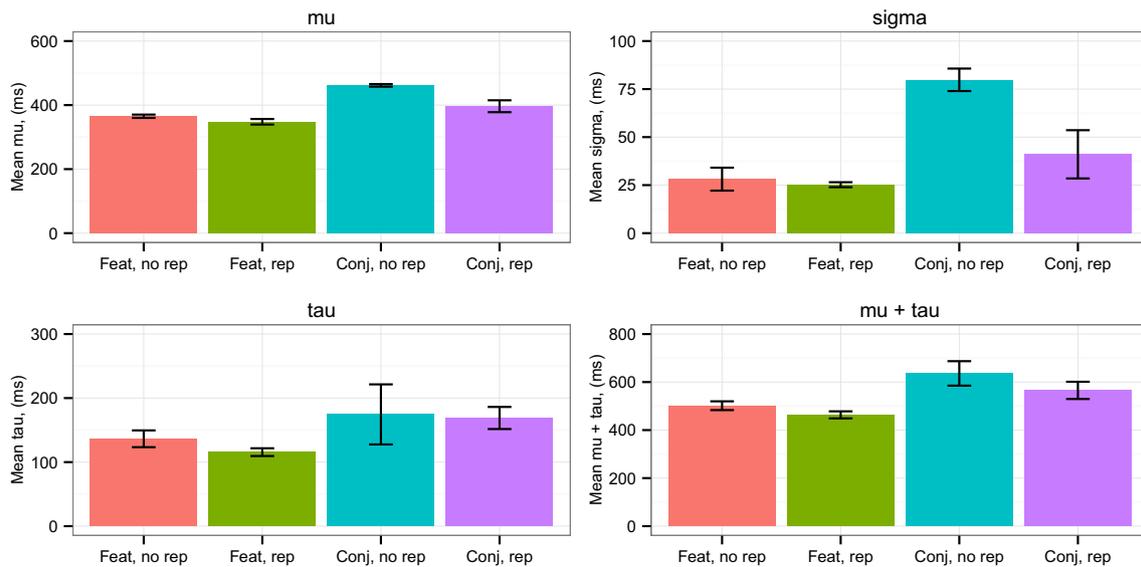
Conjunction search task

Figure 6 shows summaries of the results for the conjunction search. In a linear mixed model with both Set Size and Repetition as factors, both main effects were significant ( $t=8.1$  and  $8.0$ , respectively), but their interaction was not ( $t=0.7$ ). Again, the RT patterns indicate that this conjunction search task yields strong priming effects, as we expected from previous results (Kristjánsson & Driver, 2008; Kristjánsson, Óladóttir, & Most, 2013; Wang et al., 2005). In addition, the task shows an increase in RTs as a function of set size, as is expected for conjunction search results. The slope of set

size against RT was  $5.5 \text{ ms/item}$ ,<sup>3</sup> indicating that this was an easy conjunction search task, despite considerable uncertainty about the target identity (interfering with explicit top-down guidance) and little bottom-up saliency through feature contrasts (see Wang et al., 2005, for a discussion). The error rates ranged from 1.6 % to 1.9 % for different observers.

*Ex-Gaussian fits* Figure 7 shows RT density plots and histograms for the conjunction search, and descriptive statistics for each condition. The only significant main effect of set size was on  $\tau$  ( $p=.011$ ), in agreement with Palmer et al. (2011), but set size affected neither  $\mu$ ,  $\sigma$  (both  $ps>.6$ ), nor  $\mu+\tau$  ( $p=.296$ ). A

<sup>3</sup>  $(RT_{28} - RT_{14}) / (N_{set28} - N_{set14}) \rightarrow (965 - 888) / 14 = 5.5$ .



**Fig. 10** Ex-Gaussian parameter estimates contrasting repetitions versus nonrepetitions of feature versus conjunction search for the two observers in the data set from Kristjánsson and Driver (2005, 2008). Error bars represent  $1 \times$  between-subjects SEMs

thorough analysis of set-size effects on the parameters of fitted functions can be found in Palmer et al. (2011).

The main effect of repetition condition was significant for all factors, with  $p$  values ranging from  $p < .001$  to  $p = .025$ . The analyses above were conducted separately for both set size and repetition. When both factors were put into the same model, their interaction was never significant (all  $ps > .13$ ). The main effect of set size was only significant for  $\tau$  ( $p = .001$ ; all other  $p$  values  $> .16$ ). The main effect of repetition condition was always significant (with  $p$  values ranging from  $< .001$  to  $.016$ ), except that the effect of repetition was not significant for  $\tau$  ( $p = .144$ ). Figure 8 summarizes the effects of set size and between-trial target switches versus repetitions in the conjunction condition, whereas Fig. 9 shows the ex-Gaussian fits for individual observers.

**Discussion: Conjunction search results** To summarize, repetition of conjunction search has a strong effect on all of the parameters of the ex-Gaussian distribution, although the effect on  $\tau$  was only marginally significant for the set size of 14. These repetition effects were seen not only for the  $\mu$  and  $\tau$  parameters of the ex-Gaussian distribution, but also for the  $\sigma$  parameter, in strong contrast to the feature search results. This notable difference between the repetition effects in conjunction and feature search indicates that caution must be used when priming effects from different tasks (such as conjunction and feature searches) are compared at face value, and it suggests that different mechanisms may, at least partly, underlie the repetition effects for the two different search types.

### Addressing an alternative explanation of differences in $\sigma$ with reanalyses of data from Kristjánsson and Driver (2005, 2008)

Although the results for the different searches suggest that the  $\sigma$  parameter is differentially affected by repetition in the two search types, a potential alternative account is that other differences between the two tasks may account for the difference in  $\sigma$  estimates. The conjunction search task that we tested may have required either one or two guided searches on each trial: one if observers guessed correctly, and two if they started by looking for the wrong target initially. Priming has been shown to influence free target choice (Brascamp et al., 2011), and priming may simply bias observers to bet on the target from the last trial. If they choose the wrong target, they have to go back and search for the other possible target. This would not be the case in the feature search that we tested.

To address this question, we reanalyzed an already published data set from Kristjánsson and Driver (2005, 2008) that can address this question, since in that task feature and conjunction searches involving similar stimuli were contrasted *within the same task*. This last point is critical, since the uncertainty about target identity was comparable across searches. The only difference between the two conditions was therefore whether the target in each case could be distinguished from the distractors by a single feature.

In Kristjánsson and Driver (2008), observers searched on each trial for an odd-one-out target (see Fig. 1B). Here we contrast target-present trials only in which the exact same distractor sets were repeated between trials, but only the identity of the target changed. Thus, an example nonrepeat trial in the feature search would involve a black disk target

among white disks and white rings that followed a trial with a black ring target among white disks and white rings. A repeat trial would involve the exact same search.

An example nonrepeat conjunction search trial would involve a black disk target among black rings and white disks, preceded by a search in which the target was a white ring among black rings and white disks. In this way, we tested comparable conditions within the same task, with the only difference being whether the task involved a target that differed from the distractors on a single feature or shared a feature with each distractor set.

## Results

Figure 10 shows the results of the reanalysis fitting feature search repetitions versus conjunction search repetitions to the ex-Gaussian functions. The critical issue was whether we would find a difference in the effects of repetition between feature and conjunction searches in the effects upon  $\sigma$ . For the feature condition,  $\sigma$  is unaffected by search repetition. On the other hand, there is a large decrease in  $\sigma$  with repetition for conjunction search. The other results mirror those we saw in the preceding experiment: The  $\mu$  parameter is also more strongly affected by conjunction than by feature search repetition, as is  $\mu + \tau$ .

The results of this reanalysis of the results from Kristjánsson and Driver (2005, 2008) support our conclusions from the results of the feature and conjunction search tasks. The effects of repetition upon  $\sigma$  were minimal or absent for the feature search, but were large for the conjunction search.

## General discussion

Repetition priming of visual search strongly affects attention deployments. Understanding these effects theoretically is therefore important for a thorough understanding of how visual attention is allocated across the visual field. Measures of mean RT and variation can be ambiguous and may miss critical aspects of the effects, as was explained in the introduction. For the present purposes, our results clearly suggest that analyses of RT distributions can be informative for understanding the priming of visual search.

In particular, we found differences between feature and conjunction searches, in which the  $\sigma$  parameter was strongly affected by repetition in the conjunction but not in the feature search. Conversely, in both feature and conjunction searches, both  $\mu$  and  $\tau$  were strongly affected. One possible interpretation of this pattern is that priming during conjunction search is more likely to result in reductions in overly long RTs

than is repetition in the feature condition, thereby decreasing the variance. A straightforward interpretation of this is that priming in conjunction search decreases the number of long RTs, which in turn is likely to reflect that observers are strongly biased to the target on the last trial, decreasing the number of searches for the “wrong” target and thereby reducing the number of very long RTs.

Our investigation is by no means an exhaustive analysis of RT distributions as a function of repetition priming. Other paradigms in which attentional priming has been found should clearly also be tested.

Do the present results have any direct implications for theoretical accounts of repetition priming in visual search? This can be debated, but as many have argued before, ex-Gaussian fits can provide a three-parameter summary that is more nuanced than more traditional summary statistics. One example is the dramatic difference observed between feature and conjunction search for  $\sigma$ , clearly indicating that care must be taken when priming effects between different tasks are measured and compared. Most importantly, conjunction and feature searches cannot be compared at face value when it comes to priming effects from search repetition. On the other hand,  $\mu$  and  $\tau$  are influenced in both feature and conjunction searches. There is disagreement over how these parameters should be interpreted. We will exercise the caution recommended by Matzke and Wagenmakers (2009) and Spieler et al. (2000) in interpreting parameter values, simply noting that this suggests that repetition influences mean performance in both feature and conjunction search.

A broader message is that our results suggest that focusing too heavily on mean RTs on their own is a mistake. This has, nevertheless, been the practice in a large majority of studies of priming in visual search. There are many examples of how parameter analyses from curve fitting can inform cognitive theory, such as in Burnham (2013), who studied top-down influences on attentional capture; Heathcote et al. (1991), who studied the Stroop task; and Yap et al. (2006), who investigated RT distributions in visual word form recognition and lexical decision performance. Balota and Yap (2011) discussed how parameter fitting might influence theory—a conclusion with which we agree—and our contribution here illustrates how it can inform us on repetition effects in visual search.

We conclude that repetition priming in attentional allocation is unlikely to be explained by one single concept (as Kristjánsson & Campana, 2010, argued), nor will any single methodology answer all of the relevant questions. At the same time, parameter fits with ex-Gaussian functions can constrain theories, and matching parameters to labeled mental processes is not a prerequisite for that.

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