Journal of Experimental Psychology:
Human Perception and Performance
2012, Vol. 38, No. 3, 570–575

0096-1523/12/$12.00 DOI: 10.1037/a0027781

OBSERVATION

On the Fate of Distractor Representations

Christian Frings
University of Trier

Dirk Wentura
Saarland University

Peter Wühr
University of Dortmund

Research on the topic of distractor inhibition has used different empirical approaches to study how the human mind selects relevant information from the environment, and the results are controversially discussed. One key question that typically arises is how selection deals with the irrelevant information. We used a new selection task, in which participants sometimes had to respond to the distractors instead of the target. Importantly, we varied the time interval between stimuli onset and the cue that signaled participants to respond to the distractors. We analyzed RTs and error rates from responses to distractors as a function of how long the target had been processed (and the distractor ignored) before the cue required a response to the distractor (i.e., stimulus-cue SOA). The data are compatible with selection models assuming that distractor stimuli are initially activated and then deactivated. Thus, we argue for selection models assuming top down deactivation of distractor representations that work in parallel with top down activation of target representations.

Keywords: distractor processing, inhibition, de-activation, selective attention

Human action is usually directed toward a small subset of those objects that are simultaneously present in our environment. To support the control of actions, selective attention is assumed to facilitate the processing of action-relevant features of action-relevant objects (e.g., Allport, 1987; Neumann, 1987). Whereas it is widely agreed that attention facilitates the processing of relevant visual information by activation processes (e.g., Pashler, 1998), it is less clear how attention deals with the representation of irrelevant distractor stimuli. For example, several selection models assume that distractor representations become inhibited, at least for a short period of time (e.g., Houghton & Tipper, 1994; Schrobsdorff et al., 2007). However, both the existence and the possible characteristics of attentional inhibition are issues of considerable debate (e.g., Dagenbach & Carr, 1994; MacLeod, Dodd, Sheard, Wilson, & Bibi, 2003; Gorfein & MacLeod, 2007). The present study aims at this debate by investigating the fate of distractor representations in a new selective-attention task.

A prominent model assuming inhibitory processes is the selective-attention model of Houghton and Tipper (1994, 1996). At the core of the model are the activation values of cognitive codes representing the features of target and distractor stimuli. These stimulus codes receive activation and de-activation from different sources. The presence of the target and the distractor stimulus in the environment provides bottom-up activation for the respective codes. Moreover, the stimulus codes that match a stored template of target features receive additional activation from top-down sources, whereas the nonmatching stimulus codes receive top-down de-activation. As a result, external and internal sources will increase the activation value of the target codes, whereas external activation and internal de-activation are assumed to keep the activation value of distractor codes at resting level. A decision or response is triggered when the difference between the activation levels of target and distractor representations exceeds a threshold value.[1]

Different experimental paradigms revealed suggestive evidence for the existence of attentional inhibition, but these findings are often faced with powerful alternative explanations that do not involve inhibition (cf. Gorfein & MacLeod, 2007; Frings & Spence, 2010; MacLeod et al., 2003; Wühr & Frings,

This article was published Online First March 19, 2012.

Christian Frings, Department of Cognitive Psychology, University of Trier, Trier, Germany; Dirk Wentura, Department of Cognitive Psychology, Saarland University, Saarbrücken, Germany; Peter Wühr, University of Dortmund, Institut für Psychologie, Dortmund, Germany.

Correspondence concerning this article should be addressed to Christian Frings, Department of Cognitive Psychology, Campus I, University of Trier, D-54286 Trier, Germany. E-mail: chfrings@uni-trier.de

[1] Moreover, Houghton and Tipper assume that top-down de-activation will outlast bottom-up activation when the distractor disappears, pushing the activation of the distractor code below resting level. If the distractor re-appears as the target in a subsequent display during this “inhibitory-rebound” phase, responding to the target will be impaired compared to a neutral condition; a phenomenon called negative priming (NP; Tipper, 1985; see Tipper, 2001, for a review). Note that the present article focuses on the inhibitory processes that lead to the deactivation of the distractor representation *before* the response is made (and thereby facilitating the selection of the correct response).

2008; Mayr & Buchner, 2007). In fact, there are many attempts to explain selection without inhibition, that is, explaining selection solely based on activation processes (Cohen, Dunbar, & McClelland, 1990; Phaf, van der Heijden, & Hudson, 1990). It is possible that selective attention just facilitates the relevant information whereas the irrelevant information rests on its initial bottom-up activation, or that relevant information is activated more strongly than irrelevant information. In fact, one may assume that selective attention just amplifies the relevant information in addition to any bottom-up processes. As for the inhibition model, a decision or response can still be triggered when the difference between the activation levels of target and distractor representations exceeds a threshold value (even if the distractor representation is clearly above resting levels). It has been pointed out that models relying solely on activation processes can explain findings from selective attention tasks in a more parsimonious manner than models assuming inhibitory processes in addition to activation processes (Allport, 1987; MacLeod et al., 2003; Neumann, 1991).

The purpose of the present investigation was to provide another, more direct, test of the hypothesis that visual attention de-activates distractor codes. Therefore, we devised a new variant of the Eriksen flanker task (Eriksen & Eriksen, 1974), which taps the activation of distractors by forcing participants to sometimes respond to the distractors. In particular, participants were presented with a central target letter flanked by two incongruent, but identical distractor letters (e.g., D F D). In the majority of trials (i.e., 75%), participants responded to the central target. However, in 25% of the trials, a cue instructed participants to respond to the distractors rather than to the target. Most importantly, we varied the stimulus onset asynchrony (SOA) between stimulus onset and the cue calling for a response to the distractors.[2]

The effects of the stimulus-cue SOA on the latency and accuracy of the responses to the distractor (distractor-as-targets [DAT] performance) should—at least partially—reflect the activation values of the distractor representations at the time the cue appeared. In particular, DAT performance will comprise at least four different sources: (1) the time that is needed to switch from the preparation of the target-response to the distractor response, (2) the time that is needed for computing the distractor-response, (3) the time one has already processed the target, (4) and—most important—the benefit or cost one gains from having processed the distractor stimulus for several milliseconds while preparing the response to the target. For the sake of simplicity, we presume that switch-costs (1) and computing the distractor-response (2) are not modulated by the distractor-cue SOA. Concerning the literature on task switching (for a review Kiesel et al., 2010) one might suspect that assuming no effect of distractor-cue SOA on switch-costs is not reasonable (because the cue-stimulus SOA is known to influence switch costs). Yet, we presented the stimulus before the cue, that is, we used a negative cue-stimulus SOA, which does not modulate switch costs (Shaffer, 1965, 1966).

In the following, we describe three possible general models of distractor processing that assume or do not assume distractor inhibition, and their predictions on DAT performance (cf. Figure 1, upper panel). According to models assuming de-activation of distractor representations (e.g., Houghton & Tipper, 1994, 1996), the activation function of the distractor code should first increase (because the mere presence of distractor stimuli adjacent to the target give rise to some bottom-up activation) and then—as a result of de-activation processes—decrease again (cf. Houghton & Tipper, 1994, Figure 8, p. 82). As a result, the preactivation of the distractor will be low, then high, and then low again (cf. Figure 1). In turn, the influence of distractor preactivation on DAT performance (in terms of reaction time [RT] and accuracy) as a function of distractor-cue SOA should follow a quadratic function. In contrast, activation models, which assume a slow but linearly increasing bottom-up activation of distractor stimuli, would predict increasing DAT performance with increasing preactivation time. The more time the cognitive system already had to process the distractor stimuli, the higher the benefit from this preprocessing will be. Finally, activation models which assume a constant activation of distractor stimuli—including no activation of the distractor at all—would predict no influence of the amount of time the distractor stimulus has been processed before the cue signaled that the participants has to respond to the distractor itself. In turn, display-cue SOA should not modulate DAT performance.

Of course, these models are oversimplistic if only distractor (de-)activation is taken into account. To predict DAT performance after a switch, we should also take into account the target activation that has accumulated up to this point in time (source [3], see above). DAT performance is not only a function of current level of distractor (de-)activation, but a function of the difference between distractor and target activation (the longer the target has been processed the harder it will be to respond to the distractor). However, this additional component does not essentially alter the predicted shapes of performance functions. To start with the de-activation model, the prediction turns from a symmetric U-shaped performance function to an asymmetrically shaped function (see Figure 1, bottom panel) because linearly increasing target activation decreases DAT performance with increasing SOA. Activation Model 1 does not any longer predict improving DAT performance with increasing SOA. If we assume that target activation and distractor activation increase with the same slope, the difference is constant and DAT performance is independent from SOA. More plausible, however, is that the target activation function is steeper than the distractor activation function. Thus, the net effect will be a decreasing DAT performance. Of course, this prediction follows for activation Model 2 as well (see Figure 1, bottom

[2] We used rather short SOAs for several reasons. First, the processing (i.e., the perception and identification) of simple distractors and targets should be finished in this time window (Houghton & Tipper, 1994; Logan, 1979), and we were particularly interested in the representation of the stimuli (and their activation or deactivation). In addition, short SOAs should diminish the impact of participants' strategies (Neely, 1977; Klauer & Musch, 2003); given our task, participants might opt to prepare both responses if the stimuli are presented too long. Finally, we chose a time window which approaches the time parameters of the stop-signal paradigm (Logan, 1994) in which participants have to stop a response to a single target. Typically, participants cannot stop their response if the stop signal is presented 300 ms or later after the target onset. With a distractor-cue SOA of 200 ms or less we can be sure that the response to the target can be stopped.

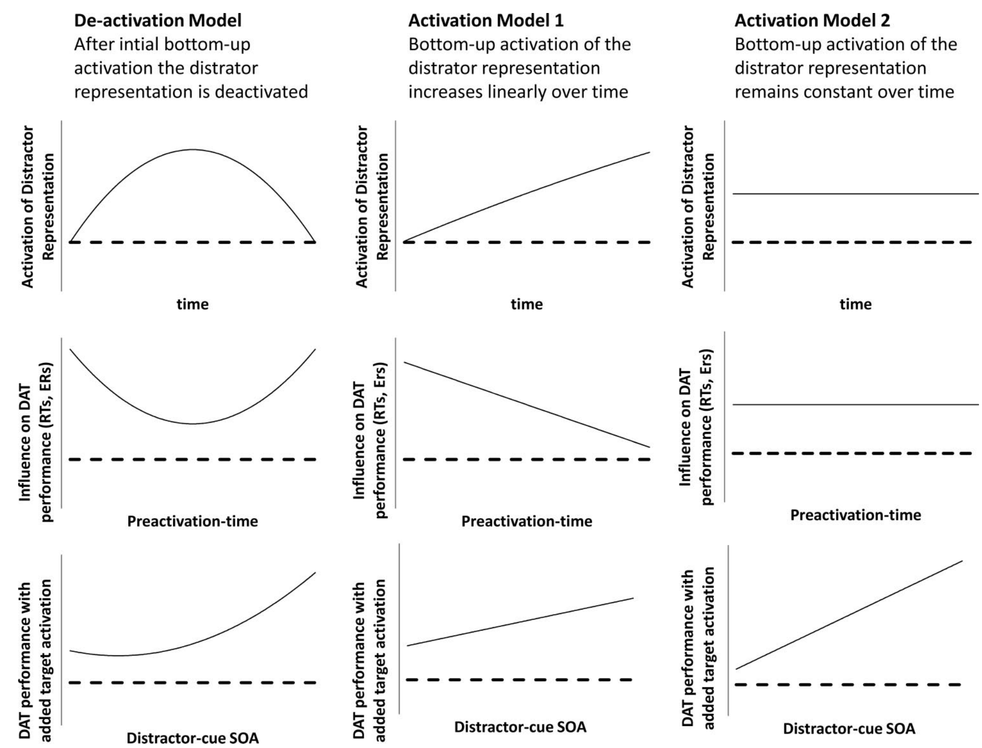

Figure 1. Three hypothetical models of distractor processing. The upper panel shows the activation of the distractor representation over time according to these models. The middle panel shows the hypothetical influence of the pre-activation of the distractor representation on distractor-as-target [DAT] performance (reaction time and error rate functions). The bottom panel shows DAT performance when an overtime increasing target activation is added. See text for further details.

panel). Note, the longer the target was processed, the harder it is to respond to the distractor. Yet, this fact is accounted by adding the target activation function to the DAT prediction.[3]

Method

Participants

Thirty undergraduate students from Saarland University took part in the experiment receiving 5 Euro for participation. Their median age was 21 (ranging from 19 to 32 years). The results from one participant were not analyzed because his average RT was an outlier when compared with the RT function of the whole sample (Tukey, 1977).

Design

Our main analyses focused on performance (i.e., RTs and error rates) in those 25% of the trials where a cue called for a response to the distractor rather than to the target. These analyses rested on a one-factorial design with the within-subjects factor SOA, which had four levels (0 ms vs. 50 ms vs. 100 ms vs. 150 ms vs. 200).

Materials and Apparatus

The experiment was conducted using standard PCs and 17″ CRT monitors. Stimuli were the letters D, F, J, and K in white on black background. Letters had a size of approximately 0.96° height and 0.76° width with a viewing distance of 60 cm. Stimuli were adjacently presented at screen center with distractor letters flanking the target (e.g., D F D).

[3] Another issue is the fact that, after the presentation of the cue, the target and the distractor change roles (i.e., the distractor becomes the ‘new target’ and vice versa). Thus, we can assume the same processes of distractor deactivation and target activation after the cue appeared (i.e., the old distractor/new target will get facilitation whereas the old target/new distractor will receive inhibition). However, this issue can be neglected because the difficulty of selecting the target versus selecting the distractor was not identical with our stimulus displays. Note that a central target was flanked by two identical distractors presented adjacent to the target. If the cue appeared and participants had to respond to the distractor, they could easily avoid the central target by shifting the attention to the left or right side. In addition, when participants responded to the distractor, they might benefit from co-activation (e.g., Fournier & Eriksen, 1990) because then there are two identical target stimuli. In sum, in our stimulus configuration selecting the target against the distractors is much harder than selecting the distractors against the target and in turn DAT performance may hinge mainly on the activation levels of target and distractor at the point in time when the cue appears but not on selection processes afterwards the cue has appeared.

Procedure

Participants were individually tested in a sound-proof chamber. Instructions were given on the screen and responses were made via a QWERTZ-keyboard. The exact sequence for each trial was as follows (cf. Figure 2): First an orientation marker ('+') was presented for 1200 ms at the screen center. Then this marker was overwritten by the target and distractor stimuli, which were presented adjacently to each other (e.g., DFD). Participants were instructed to classify the target letter as quickly and as accurately as possible by pressing the corresponding key on the keyboard. If participants' RTs were longer than 1200 ms on a given trial a warning was shown in which it was stressed that they should react as quickly as possible to targets.

However, on 25% of trials a white rectangle was presented around the stimuli (about 0.97° distance to the letters). If the rectangle appeared, participants were supposed to respond to the identity of the distractors instead of responding to the target. The time interval between stimulus onset and the rectangle was varied between 0 to 200 ms. After participants' reaction a blank screen was presented for 1000 ms. Participants were instructed to always prepare the target response; the instruction roughly followed standard instructions from the stop signal paradigm (cf. Logan, 1994). All trials were incongruent (that is flanker and target letters were always different). Overall, there were 289 experimental trials, 204 with reactions to targets and 85 with reactions to distractors (17 for each SOA condition). Sequence of trials and assignment of stimuli to the roles as target or distractors were randomly chosen. Before the experiment participants practiced the task on 68 trials (20 trials with rectangle, 4 for each SOA condition), which were identical to the experimental trials.

Results

Only correct responses with RTs above 200 ms and 1.5 interquartile ranges below the third quartile of the overall RT distribution (Tukey, 1977) were used for the RT analysis. Averaged across participants, 82% of the trials were selected for RT analysis. 15.9% of the trials were excluded because of erroneous responses; 2.1% of the trials were excluded because of the RT-outlier criterion (1,488 ms; Tukey, 1977). Mean RTs and error rates are depicted in Table 1.

Response Times to Distractors

RTs from error-free responses to distractors were subjected to a repeated measures multivariate analysis of variance (MANOVA) with the single factor SOA (0, 50, 100, 150, and 200 ms). The main effect of SOA was significant, $F(4, 25) = 16.24$, $p < .001$, $\eta_p^2 = .72$, indicating that RTs varied across SOA. More interestingly, the time-course of RTs to distractors exhibited a significant quadratic trend (see Figure 3), $F(1, 28) = 22.63$, $p < .001$, $\eta_p^2 = .45$. When the SOA increased, RTs first decreased from 1,034 ms (SOA = 0 ms) to 1019 ms (SOA = 100), and then increased to 1135 ms (SOA = 200 ms).

Percentages of Errors to Distractors

The SOA variable also had a significant effect on error percentages, $F(4, 25) = 3.21$, $p < .05$, $\eta_p^2 = .34$. Similar to RTs, the time course of the error rates exhibited a significant quadratic shape, $F(1, 28) = 11.86$, $p < .001$, $\eta_p^2 = .30$ (see Figure 3).

RTs and Error Percentages to Targets

Participants' RTs to targets (M = 788 ms) were shorter than RTs to distractors (M = 1035 ms), $F(1, 28) = 589.56$, $p < .001$,

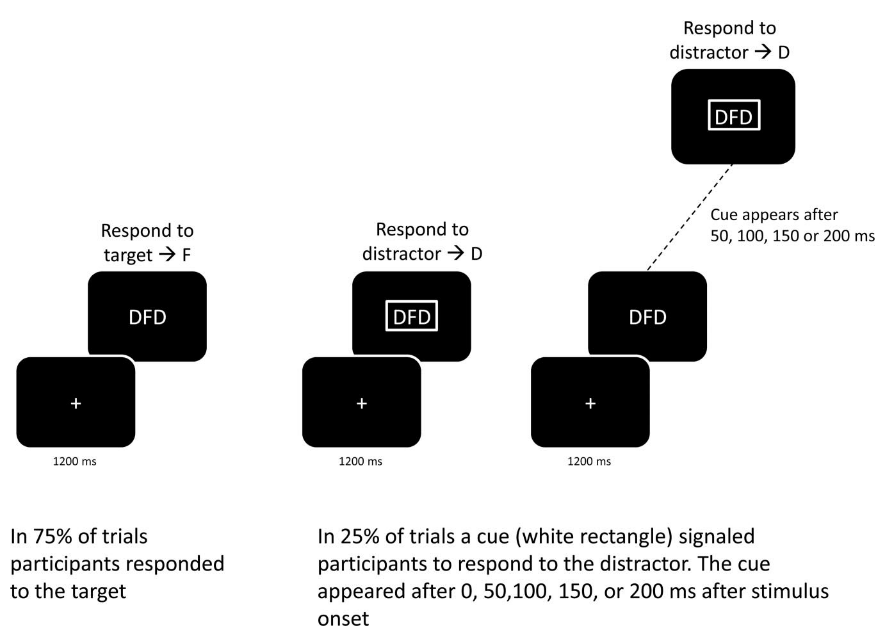

Figure 2. A schematic display of the trials used in Experiment 1. Targets were presented between distractors. Stimuli are not drawn to scale.

Table 1
Reaction Times (in Milliseconds) and Error Rates (in Percentage) for Responses to Incongruent Distractors as a Function of Distractor-Cue SOA

	Distractor-Cue SOA				
	0 ms	50 ms	100 ms	150 ms	200 ms
RT	1034	996	1019	1081	1136
ER	31.4	23.3	22.7	25.6	29.8

Note. RT = reaction time; ER = error rate.

$\eta_p^2 = .96$. Moreover, participants' responses to targets were more accurate ($M = 88.6\%$ correct responses) than their responses to distractors ($M = 73.4\%$ correct responses), $F(1, 28) = 44.95$, $p < .001$, $\eta_p^2 = .62$.

Discussion

Dual-process models of attention, which assume both amplification of target processing and inhibition of distractor processing, predict a quadratic trend in the functions relating the latencies (or error rates) of responses to distractor stimuli. In contrast, single-process models, which exclude inhibitory mechanisms, rather predict more linear performance functions in response to distractor stimuli. The data pattern observed with our new task was in line with models assuming deactivation of distractors.

Interestingly, the patterns of DAT performance slightly deviate for RTs and errors. The RT pattern clearly followed the prediction that derives from combining the quadratic distractor activation function and the linear increasing target activation function (see Figure 1, bottom panel), whereas the error curve directly mirrors the distractor activation function (see Figure 1,

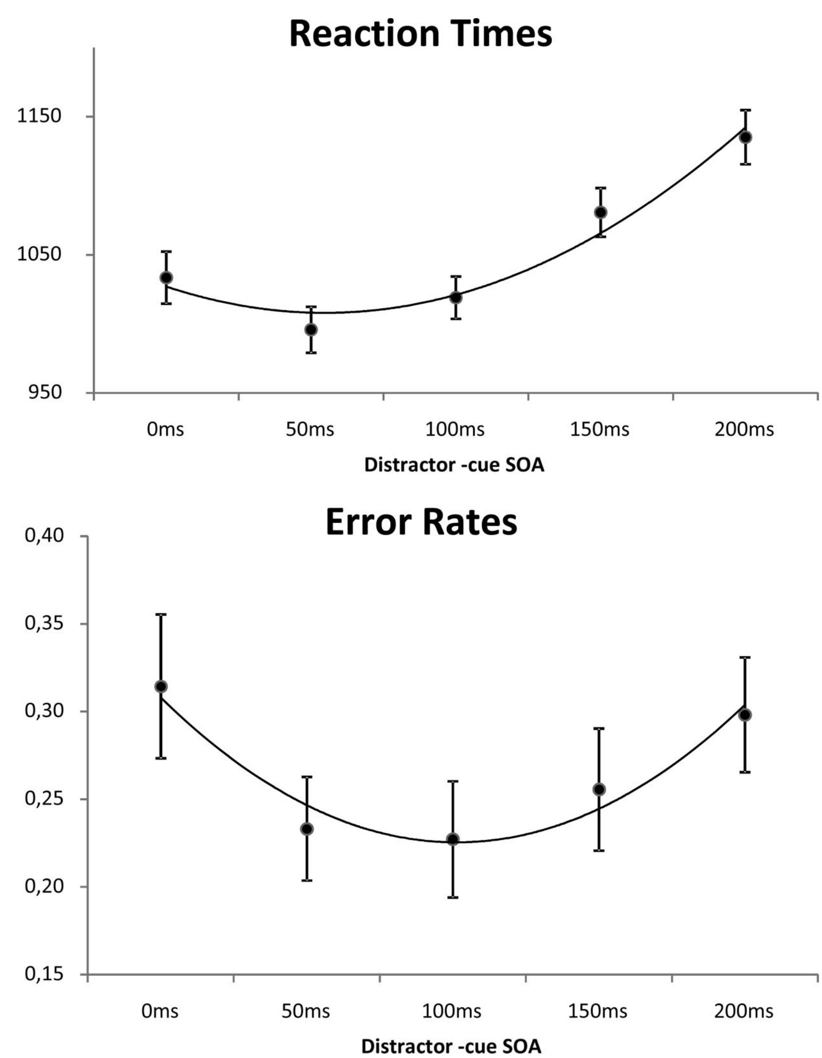

Figure 3. Reaction time function (upper panel) and the error function (lower panel) of responses given to incongruent distractors as a function of the distractor-cue SOA. The trend lines depict the quadratic trend. Error bars represent standard error of the mean.

middle panel). This puzzle is resolved by considering that the RT and error rate function of DAT performance measure two slightly different aspects here. In particular, in trials where participants *correctly* respond to the distractor, the difference in activation between the distractor and the target influence the response, that is, for a correct response the response threshold (a particular difference in activation) must be achieved. The response threshold is directly influenced by the activation level of the target. Thus in turn the linearly increasing target function combined with the quadratic distractor activation function leads to an asymmetrical RT function. However, in trials with an *erroneous* response, participants respond *before* any difference in activation between the target and distractor has reached the response threshold as to respond correctly. Thus, the likelihood with which the participant responds with the distractor-key (i.e., the new target) is directly determined by the activation level of the distractor. If the distractor representation is highly activated, the probability of pressing the distractor-key is higher (leading to less errors) as compared with trials in which the distractor activation is low (leading to more errors). In other words, the error rate may reflect the activation of the distractor in a purer fashion as compared to the RT function.

In conclusion, our results obtained with a novel task provide evidence for dual-process theories of attention in general, and distractor-deactivation in particular. The quadratic shape of performance functions are exactly what deactivation models would predict, whereas single-process models assuming only activation processes cannot explain the observed data pattern.

References

Allport, D. A. (1987). Selection for action: Some behavioural and neurophysiological considerations of attention and action. In H. Heuer & A. F. Sanders (Eds.), *Perspectives on perception and action* (pp. 395–419). Hillsdale, NJ: Erlbaum.

Cohen, J. D., Dunbar, K., & McClelland, J. L. (1990). On the control of automatic processes: A parallel distributed processing account of the stroop effect. *Psychological Review, 97,* 332–361. doi:10.1037/0033-295X.97.3.332

Dagenbach, D., & Carr, T. H. (1994). Inhibitory processes in perceptual recognition: Evidence for a center-surround attentional mechanism. In D. Dagenbach & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 327–357). San Diego, CA: Academic Press.

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics, 16,* 143–149. doi:10.3758/BF03203267

Fournier, L. R., & Eriksen, C. W. (1990). Coactivation in the perception of redundant targets. *Journal of Experimental Psychology: Human Perception and Performance, 16,* 538–550. doi:10.1037/0096-1523.16.3.538

Frings, C., & Spence, C. (2011). Increased perceptual and conceptual processing difficulty makes the immeasurable measurable: Negative priming in the absence of probe distractors. *Journal of Experimental Psychology: Human Perception and Performance, 37,* 72–84. doi:10.1037/a0020673

Gorfein, D. S., & MacLeod, C. M. (Eds.). (2007). *Inhibition in cognition.* Washington, DC: American Psychological Association. doi:10.1037/11587-000

Houghton, G., & Tipper, S. P. (1994). A model of inhibitory mechanisms in selective attention. In D. Dagenbach & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 53–112). San Diego, CA: Academic Press.

Houghton, G., & Tipper, S. P. (1996). Inhibitory mechanisms of neural and cognitive control: Applications to selective attention and sequential action. *Brain and Cognition, 30,* 20–43. doi:10.1006/brcg.1996.0003

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Phillip, A., & Koch, I. (2010). Control and interference in task switching - A review. *Psychological Bulletin, 136,* 849–874. doi:10.1037/a0019842

Klauer, K. C., & Musch, J. (2003). Affective priming: Findings and theories. In J. Musch & K. C. Klauer (Eds.), *The psychology of evaluation: Affective processes in cognition and emotion* (pp. 7–49). Mahwah, NJ: Lawrence Erlbaum.

Logan, G. D. (1979). On the use of a concurrent memory load to measure attention and automaticity. *Journal of Experimental Psychology: Human Perception and Performance, 5,* 189–207. doi:10.1037/0096-1523.5.2.189

Logan, G. D. (1994). On the ability to inhibit thought and action: A user's guide to the stop signal paradigm. In D. Dagenbach, & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 189–239). San Diego, CA: Academic Press.

MacLeod, C. M., Dodd, M. D., Sheard, E. D., Wilson, D. E., & Bibi, U. (2003). In opposition to inhibition. In B. H. Ross (Ed.), *The psychology of learning and motivation* (Vol. 43, pp. 163–214). San Diego, CA: Academic Press.

Mayr, S., & Buchner, A. (2007). Negative priming as a memory phenomenon: A review of 20 years of negative priming research. *Zeitschrift für Psychologie/Journal of Psychology, 215,* 35–51.

Neely, J. H. (1977). Semantic priming and retrieval from lexical memory: Roles of inhibition-less spreading activation and limited-capacity attention. *Journal of Experimental Psychology: General, 106,* 226–254. doi:10.1037/0096-3445.106.3.226

Neumann, O. (1987). Beyond capacity: A functional view of attention. In H. Heuer & A. F. Sanders (Eds.), *Perspectives on perception and action* (pp. 361–394). Hillsdale, NJ: Lawrence Erlbaum.

Neumann, O. (1991). *Konzepte der Aufmerksamkeit: Entstehungen, Wandlungen und Funktionen eines psychologischen Begriffs.* Munich, Germany: Unveröffentlichte Habilitationsschrift, Ludwig-Maximilians University.

Pashler, H. (1998). *The psychology of attention.* Cambridge, MA: MIT Press.

Phaf, R. H., Van der Heijden, A. H. C., & Hudson, P. T. (1990). SLAM: A connectionist model for attention in visual selection tasks. *Cognitive Psychology, 22,* 273–341. doi:10.1016/0010-0285(90)90006-P

Schrobsdorff, H., Ihrke, M., Kabisch, B., Behrendt, J., Hasselhorn, M., & Herrmann, J. M. (2007). A computational approach to negative priming. *Connection Science, 19,* 203–221. doi:10.1080/09540090701507823

Shaffer, L. H. (1965). Choice reaction with variable S-R mapping. *Journal of Experimental Psychology, 70,* 284–288. doi:10.1037/h0022207

Shaffer, L. H. (1966). Some effects of partial advance information on choice reaction with fixed or variable S-R mapping. *Journal of Experimental Psychology, 72,* 541–545. doi:10.1037/h0023749

Tipper, S. P. (1985). The negative priming effect: Inhibitory priming by ignored objects. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology, 37,* 571–590.

Tipper, S. P. (2001). Does negative priming reflect inhibitory mechanisms? A review and integration of conflicting views. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology, 54,* 321–343. doi:10.1080/713755969

Tukey, J. W. (1977). *Exploratory data analysis.* Reading, MA: Addison-Weasley.

Wühr, P., & Frings, C. (2008). A case for inhibition: Visual attention suppresses the processing of irrelevant objects. *Journal of Experimental Psychology: General, 137,* 116–130. doi:10.1037/0096-3445.137.1.116

Received September 14, 2011
Revision received January 30, 2012
Accepted January 31, 2012 ■