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Effects of Spatial and Selective Attention on Basic Multisensory Integration

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When participants respond to auditory and visual stimuli, responses to audiovisual stimuli are substantially faster than to unimodal stimuli (redundant signals effect, RSE). In such tasks, the RSE is usually higher than probability summation predicts, suggestive of specific integration mechanisms underlying the RSE. We investigated the role of spatial and selective attention on the RSE in audiovisual redundant signals tasks. In Experiment 1, stimuli were presented either centrally (narrow attentional focus) or at 1 of 3 unpredictable locations (wide focus). The RSE was accurately described by a coactivation model assuming linear superposition of modality-specific activation. Effects of spatial attention were explained by a shift of the evidence criterion. In Experiment 2, stimuli were presented at 3 locations; participants had to respond either to all signals regardless of location (simple response task) or to central stimuli only (selective attention task). The RSE was consistent with task-specific coactivation models; accumulation of evidence, however, differed between the 2 tasks.

Keywords: multisensory processes, spatial attention, selective attention

Visuospatial attention is often seen in an analogy to a spotlight which means that stimuli falling into this spotlight are processed more efficiently at the cost of those that do not (Posner, Snyder & Davidson, 1980; Cave & Bichot, 1999). When attention is zoomed in, perception of stimuli at the center of focus becomes more efficient; the greater the distance to this focus, the less efficient perception becomes (Castiello & Umiltà, 1990). Traditionally, selective spatial attention has been studied with auditory stimuli (e.g., Broadbent, 1952) or with visual stimuli (Posner, 1980). However, everyday perception is mostly multisensory in nature. As different sensory systems provide complementary, redundant, or conflicting information (Welch & Warren, 1986), effective behavior requires integration of the sensory signals provided by the different senses. Thus, research effort has been directed to investigate the role of attention in multisensory, especially audiovisual (Driver, 1996; Spence & Driver, 1997) and visuotactile perception (Macaluso, Frith & Driver, 2000). One of the most fundamental questions that arise with spatial attention is whether there exists a common, supramodal attentional system or several, independent subsystems. With cueing paradigms, Spence and Driver (1997) demonstrated that visuospatial attention can be directed by auditory cues. On the other hand, some degree of independence has also been found between attentional resources of different sensory systems (Alais, Morrone & Burr, 2006). While it is widely accepted that spatial attention is a multisensory phenomenon, the exact role of attention in multisensory perception still remains unclear.

In research on multisensory processes, the most basic experimental setup is the bimodal redundant signals paradigm: Participants are asked to respond in the same way to stimuli of two different modalities (e.g., auditory and visual, A, V). In some trials, both stimuli are presented (AV), and this stimulus combination is referred to as the redundant signals condition. In the redundant signals condition, responses are usually substantially faster than in the single target conditions (e.g., Raab, 1962).

At first glance, this so-called redundant signals effect (RSE, e.g., Kinchla, 1974) might be taken as sufficient evidence for the existence of genuine multisensory integration mechanisms. However, different processing architectures can account for redundancy gains in such tasks; the most important model classes are race models (or, more generally, separate activation models, e.g., Raab, 1962) and coactivation models (Miller, 1982). In the race model, both components of a bimodal stimulus are processed in parallel channels; the overall processing time is determined by the channel which has first finished processing (e.g., having reached a threshold first). This mechanism eliminates slow processing times from the modality-specific distributions, which, on average, results in faster responses to bimodal events. The redundancy gain of the race model has an upper limit, though; this upper limit is known as the race model inequality (Miller, 1982):

$$F_{AV}(t) \leq F_A(t) + F_V(t), \text{ for all } t, \qquad (1)$$

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with $F(t) = P(\mathbf{T} \leq t)$ denoting the probability for a response latency $\mathbf{T}$ within t ms. In bimodal divided attention, response times for AV have often been observed to violate Inequality 1.

Instead, coactivation models have been proposed which specify a more or less explicit integration mechanism (Miller, 1982, App. A; Miller, 1986, Eq. 3; Schwarz, 1989, 1994; Diederich, 1995; Miller & Ulrich, 2003). Several coactivation models assume linear superposition of modality-specific information (Schwarz, 1989, 1994; Diederich, 1995; Miller & Ulrich, 2003). Let $\mathbf{X}_A(t)$, $\mathbf{X}_V(t)$ denote the stochastic processes describing the buildup of evidence in the auditory and visual channel, respectively. Superposition models assume that the activation of the combined channels corresponds to the sum of the two sensory-specific channels, $\mathbf{X}_{AV}(t) = \mathbf{X}_A(t) + \mathbf{X}_V(t)$. Detection occurs whenever an evidence criterion c is surpassed for the first time. For time-homogenous diffusion processes underlying the channel-specific buildup of evidence $\mathbf{X}_A(t)$, $\mathbf{X}_V(t)$, Schwarz (1994) derived predictions for the mean and the variance of the detection time $\mathbf{D}$ for unimodal and bimodal stimuli presented simultaneously, or with onset asynchrony τ:

$$E[\mathbf{D}_A] = c/\mu_{A,}$$

$$E[\mathbf{D}_V] = c/\mu_{V,}$$

$$E[\mathbf{D}_{AV}] = c/(\mu_A + \mu_V),$$

$$E[\mathbf{D}_{A(\tau)V}],\ E[\mathbf{D}_{V(\tau)A}]\text{: see Schwarz (1994, Eq. 10)}, \qquad (2)$$

with μ_A, μ_V denoting the drift rates of the modality-specific diffusion processes, and $c > 0$ denoting an absorbing barrier (i.e., the evidence criterion). Assuming a SOA invariant μ_M summarizing the mean duration of processes not described by the model, Schwarz (1994, Figure 1) demonstrated that the diffusion superposition model well described the mean response Times $E(\mathbf{T}) = E(\mathbf{D}) + \mu_M$ observed by Miller (1986) in a simple speeded response task with audiovisual stimuli presented at different onset asynchronies (for the standard deviations, see Schwarz, 1994, Figure 2).

The present study investigates the integration of redundant signals under different attentional conditions on the basis of the diffusion superposition model. It is usually assumed that "integration" requires spatial attention; for example, to solve the binding problem in visual object perception as posited by the feature integration theory (Treisman & Gelade, 1980; Treisman, 1986). In the dimensional action model, which incorporates many ideas of the feature integration theory, attention plays a central role (Cohen & Shoup, 1997). The model assumes that properties of a visual stimulus are decomposed into a number of dimensional modules (e.g., for form, color, orientation, etc.). Each dimensional module detects the presence or absence of features in its respective dimension. The activation elicited by these features is then transmitted to dimension-specific response selection processors (Cohen & Feintuch, 2002). For redundant signals of the same dimension, the model predicts only limited redundancy gains, because both stimuli activate only a single response selector (e.g., Miller, Beutinger, & Ulrich, 2009). In redundant signals of different dimensions, however, two response selectors are simultaneously active, yielding especially fast responses. Indeed, Feintuch and Cohen (2002) observed that response time distributions for redundant color-orientation targets violate the race model inequality (1), however, only if the stimulus components were presented in close spatial proximity such that participants could direct spatial attention to the location of the target.

By analogy, one would expect that spatial attention is necessary for multisensory coactivation, as well. However, the role of attention in multisensory integration remains controversial (e.g., Navarra, Alsius, Soto-Faraco, & Spence, 2010). It has been argued that connections between auditory and visual cortices are so abundant that multisensory integration processes do not require spatial attention (Bertelson, Vroomen, de Gelder, & Driver, 2000). Moreover, multisensory processing can precede attentional allocation (Driver, 1996). On the other hand, spatial attention has been shown to affect the earliest multisensory components of the event-related potential (Talsma, Doty, & Woldorff, 2007), which at least suggests that attention is involved in multisensory integration processes.

Concerning the redundant signals effect, the exact role of attention in effective integration is not yet fully understood (Miller et al., 2009). It is known that under some circumstances, attention can be assigned to more than one location at a time (Castiello & Umiltà, 1992; McCormick, Klein, & Johnston, 1998; Dubois, Hamker, & VanRullen, 2009). This split of spatial attention is advantageous in the sense that a series of locations do not have to be attended to in a serial manner. The advantage comes at a cost; however, splitting spatial attention means dividing resources, leaving less beneficial effects of attention the more locations one is assigning attention to (Castiello & Umiltà, 1992). It remains unclear whether the attentional spot is enlarged or simply fewer focused to encompass all target locations (e.g., those indicated by cues), or if the attentional system is capable of dividing the attentional focus to several locations simultaneously (Bichot, Cave, & Pashler, 1999).

In the present study, we directly compared two conditions of spatial attention (narrow focus, wide focus) in a redundant signals experiment using audiovisual stimuli with varying onset asynchronies between the auditory and visual stimulus components (Experiment 1). The obtained mean response times were then modeled with a diffusion model of the redundant signals effect (Schwarz, 1994), separately for both attentional conditions. In line with earlier results, we expected that the diffusion superposition model can describe the redundancy gains in the narrow focus condition. We additionally applied a common model to identify similarities and differences in audiovisual perception for the different levels of spatial attention. Whereas elementary modality-specific perception to the same stimuli can be expected to be similar, it is unclear whether the same superposition mechanism holds for the two attentional conditions.

In a second experiment, we used the same diffusion model approach to compare mean reaction times of simple responses with those of selective attention. In this experiment, stimulation was exactly the same under both conditions, but for the selective attention condition, observers were instructed to attend to only one location and to disregard stimuli at the other locations. Earlier results (Gondan, Götze, & Greenlee, 2010) obtained from a Go/Nogo task indicate that coactivation cannot be taken for granted in tasks more complex than speeded responses. The main question addressed by Experiment 2 was, therefore, whether the superposition model can explain redundancy gains in a selective attention task, and if so, whether modality-specific processing is qualitatively the same for the different tasks.

Experiment 1

In Experiment 1, participants made speeded responses to auditory, visual, and audiovisual signals presented with onset asynchrony. In the narrow focus condition, stimuli were presented at a single central position only; here participants could concentrate on the source of stimulation. In the wide focus condition, stimuli were presented randomly at one of three possible locations (left, right, center), such that participants had to enlarge their attentional spotlight in order to attend to all three locations.

Methods

Participants. Four right-handed volunteers (3 students from the University of Regensburg, one male, two female, mean age 22 years, and one author) participated in the experiment. All reported normal hearing and normal or corrected-to-normal visual acuity with an intact field of view. Except for the coauthor, the participants were naive regarding the purpose of the experiment and the stimulus conditions employed. Informed consent was obtained from all participants prior to participation. Results were stored in anonymous form. Participants received course credit or payment (7€ per hour) for their participation. The experiment was conducted in accordance to the standards laid down in the Declaration of Helsinki.

Apparatus. The experiment was conducted in a light- and sound-proof room (Industrial Acoustics Company GmbH, Niederkrüchten, Germany), which was dimly illuminated from behind and above. The participants were directly facing the stimulation device, which was placed on a desk at a distance of 60 cm. The device consisted of a projection screen for the visual stimuli and three mobile loudspeakers for the auditory stimuli, which had been placed on elevated platforms in the central position and the outer left and outer right side of the desk. Stimulus presentation and response time recording was controlled by a standard personal computer running "Presentation" (Neurobehavioral Systems, Albany, California).

Stimuli. A Gabor-patch was projected at three different positions on a uniform gray background using a luminance-calibrated liquid crystal display projector: the center, the outer left, and the outer right (angle 30° each) side of the screen. White noise (50 dB) served as the auditory stimulus and was emitted via three loudspeakers in the same central, left, and right positions (not visible to the participant). Audiovisual signals were presented in spatial correspondence, at 13 stimulus onset asynchronies (SOAs, cf. Miller, 1986): A, A167V, A133V, A100V, A67V, A33V, AV, V33A, V67A, V100A, V133A, V167A, and V (SOA in ms). Catch trials (C, i.e., trials in which no stimulus appeared at the usual stimulus onset) were embedded in the experimental procedure to discourage anticipatory guesses. The interstimulus interval varied uniformly between 2100 ms and 3000 ms. Participants had to respond to the stimuli by pressing a response button with their dominant hand.

Experimental tasks. In the wide focus condition (WID), the participants were told to respond as quickly as possible to any detected signal at any possible position (left, center, right). Because the participants did not know the position at which the stimulus would appear, they had to spread their attention over all three locations. In the narrow focus condition (NAR), stimuli appeared only in the center of the screen or from the central loudspeaker. Here, participants knew the position at which the stimuli would appear, so they could concentrate on this position.

Procedure. Each participant was tested in three sessions of about 3 hours each. At the start of the experiment, the participants were instructed and a training block was run with the same stimulus protocol as used in the main session. The main session was divided into 13 blocks of 10 min each. Breaks were made on request of the participants; usually participants requested a break of 20 to 30 min at the middle of the session. Each block comprised both experimental tasks, so each block started with a screen indicating the current experimental condition, the WID or NAR. The participants had to fixate a plus (+) sign which appeared at the center of the screen during the interstimulus intervals. In both tasks, the stimuli were presented in a randomized sequence. Each of the 3 (WID)/1 (NAR) locations × SOA stimulus conditions appeared three times within each block, yielding a maximum of 110 replications per experimental condition.

Test of the race model. The race model inequality was tested after cleaning the response time distributions of the different conditions using the "kill-the-twin" procedure (Eriksen, 1988). In the kill-the-twin procedure, the response time distribution for catch trials $F_C(t) = P(\mathbf{T}_C \leq t)$ is subtracted from the response time distributions of all SOA-specific conditions (Gondan & Heckel, 2008). For Condition V(τ)A, the modified inequality, thus, reads as

$$[F_{V(\tau)A}(t) - F_C(t)] \leq [F_V(t) - F_C(t)] + [F_A(t-\tau) - F_C(t-\tau)], \text{ for all } t. \quad (3)$$

Miller (1986) suggested to measure the amount of violation of Inequality 3 by the positive area enclosed by the AV curve and the summed A and V curves. We used a nonparametric variant of this area based on the rank-transformed data,

$$\Delta_\tau = \Sigma^{N}_{i=1} \max\{0, [F_{V(\tau)A}(t_i) - F_C(t_i)] - [F_V(t_i) - F_C(t_i)] - [F_{(\tau)A}(t_i) - F_{(\tau)C}(t_i)]\},$$

with $F_{(\tau)A}$ denoting the shifted response time distribution for auditory stimuli. This measure is scale-invariant and robust with regard to outliers. The violation area was measured in all SOA conditions and collapsed into an aggregate violation area by a weighted sum $\Delta = \Sigma_\tau\, \lambda(\tau) \times \Delta_\tau$, with $\lambda(\tau) > 0$ denoting a triangular weighting function assigning weights 1, 2, 3, 4, 5, 6, 5, 4, 3, 2, 1 to Conditions A167V, A133V, A100V, A67V, A33V, AV, V33A, V67A, V100A, V133A, V167A, respectively ("symmetric umbrella," Gondan, 2009). To test whether $\Delta > 0$ observed in a given participant reflects true coactivation or is due to sampling error, 10,000 computer simulations were performed (Miller, 1986). In each simulation, bootstrap samples of the unimodal response times were drawn from the observed response time distributions, bimodal response times were bootstrapped from the distribution of minima of the unimodal response times, adjusted for SOA and assuming a maximally negative channel correlation between A and V (Ulrich & Giray, 1986). In each simulation, the aggregate violation area Δ^* was determined, resulting in 10,000 simulated Δ^*. The race model is rejected at $p < .05$, if the observed Δ is greater than 95% of the Δ^* values under the race model assumption.

Diffusion superposition model. The diffusion superposition model predicts the mean response times for audiovisual stimuli with given SOA τ using five free parameters: drift and variance of the auditory (μ_A, σ_A^2) and the visual process (μ_V, σ_V^2), and a mean residual μ_M summarizing everything not described by the model. In the task-specific models, the barrier *c* was fixed at 100, since it only scales the other parameters.

For the model fit, trimmed mean response times were used, excluding the upper and the lower 2% of the response times, separately for each condition. Goodness-of-fit χ^2 was calculated by adding up the squared standardized differences X_τ^2 between model prediction $E[\mathbf{T}_{V(\tau)A}]$ and observed mean response time $m_{V(\tau)A}$ for each SOA:

$$\chi^2 = \Sigma_\tau X_\tau^2 = \Sigma_\tau\{m_{V(\tau)A} - E[\mathbf{T}_{V(\tau)A}]\}^2/\{\hat{s}^2_{V(\tau)A}/n_{V(\tau)A}\}, \quad (4)$$

with $\hat{s}^2_{V(\tau)A}/n_{V(\tau)A}$ denoting the square of the observed standard error. If the model holds, the means $m_{V(\tau)A}$ are approximately normally distributed around $E[\mathbf{T}_{V(\tau)A}]$, and, thus, for large $n_{V(\tau)A}$, the squared standardized means converge to an approximate χ_1^2 distribution. As the five model parameters are adjusted to the means observed in 13 SOAs, the sum of the SOA-specific X_τ^2 values approximately follows a χ^2 distribution with $13 - 5 = 8$ degrees of freedom. The model was adjusted to the observed mean response times by minimizing (4) using the constrOptim command of the R statistical language (R Development Core Team, 2010) with restrictions $0.1 \leq \mu_A, \mu_V \leq 4$, $10 \leq \sigma_A^2, \sigma_V^2 \leq 10{,}000$, $100 \leq \mu_M \leq 1000$.

In a first step, separate models were adjusted to the mean response times observed in the two tasks. As stated above, for the WID, only the responses to central stimuli were analyzed. In a second step, an aggregate model was adjusted to mean response times of both the NAR and the WID (central stimuli only). In this aggregate model, diffusion parameters were assumed to be equal for both tasks; task-specific processing and attentional demands were taken into account by allowing different evidence criteria c_{WID} and c_{NAR} for the two tasks ($c_{WID} = 100$, c_{NAR}: variable).

Results

In the NAR, participants knew that stimuli were presented at the central location only; whereas in the WID, stimulus presentation was randomized, with one third of the stimuli presented left or right or at the central position. Direct comparison of the response times in the two tasks is, thus, most informative for centrally presented stimuli. For these stimuli, mean response times for Participants 1, 2, 3, and 4 were lower in the NAR than in the WID (averaged over SOA, 17, 31, 14, 13 ms for Participant 1, 2, 3, and 4, respectively). Within both tasks, mean response times showed a wing-shaped pattern (see Figure 1), replicating the usual relationship between SOA and mean response time observed in redundant signals tasks with asynchronous targets (Ulrich & Miller, 1997; Schwarz, 1994). Omissions and responses to catch trials were extremely rare (false alarm rate 0%, omission rate around 1%) and were, thus, not further analyzed.

Race model. After correction for fast guesses using the kill-the-twin procedure (Eriksen, 1988), violation areas of the race model inequality were obtained for each SOA and added up using a symmetric umbrella weighting function (Gondan, 2009). These observed summed violation areas were compared with their bootstrap distribution under the race model assumption (Miller, 1986). Consistent violations of the race model inequality were observed for the WID (*p* values of bootstrap test .026, .040, .014, $< .001$ for Participants 1, 2, 3, and 4, respectively). In the NAR, violations of the race model inequality reached statistical significance for three participants ($p = .003, .180, < .001, < .001$ for Participants 1, 2, 3, and 4, respectively).

Diffusion superposition model. In a first step, task-specific diffusion superposition models were adjusted to the mean response times observed in the WID and NAR. Fitted parameters for these models are shown in Table 1. In line with the substantially lower mean reaction times for auditory stimuli, the drift rates for the auditory process are higher than for the visual process. The task-specific models show acceptable goodness-of-fit in all participants (summarized goodness-of-fit statistic for the WID: $\chi^2 = 44.92$, $df = 32$, $p = .064$; for NAR: $\chi^2 = 20.98$, $df = 32$, $p = .932$).

In a second step, an aggregate model was adjusted to the mean response times for both tasks, with common parameters describing the diffusion processes and the residual, but different evidence barriers ($c_{WID} = 100$ fixed, $c_{NAR} < 100$) for the two tasks. Figure 1 illustrates the good agreement between predicted and observed mean response times in the two tasks. The aggregate model adequately describes the observed mean response times ($\chi^2 = 106.55$, $df = 80$, $p = .025$); however, model fit is poor in one participant (right panel of Figure 1).

Discussion

Our goal of the first experiment was to investigate whether and how redundancy gains are affected by spatial attention. Abstract artificial stimuli were used which are known to be very effective in their respective modalities. Participants had to perform a simple response task to audiovisual target stimuli under two attentional conditions. In the NAR (narrow focus), stimuli were presented at a constant predictable location in the center of fixation. In the WID (wide focus), stimuli were presented randomly at one of three different locations. The central stimuli used in the two attentional conditions had the same physical properties. In the NAR, participants could concentrate on the central location, whereas in the WID, participants had to attend to all three locations simultaneously.

Indeed, mean response times were lower in the NAR as compared with the same stimuli in WID. The magnitude of the attention effect was, however, small in terms of absolute reaction times (see Figure 1). Although the attentional requirements differed for the NAR and the WID, the participants were asked to fixate the central location in both conditions. Therefore, it cannot be ruled out that participants actually concentrated more on the central position in the WID than on the two peripheral positions. This would explain the rather small attention effect in Experiment 1. Except for one participant, the test of the race model inequality revealed significant violations of the race model inequality in both the NAR and the WID, indicative of coactive processing of the redundant information.

In the first step of the main analysis, task-specific diffusion superposition models (Schwarz, 1994) were adjusted to the mean

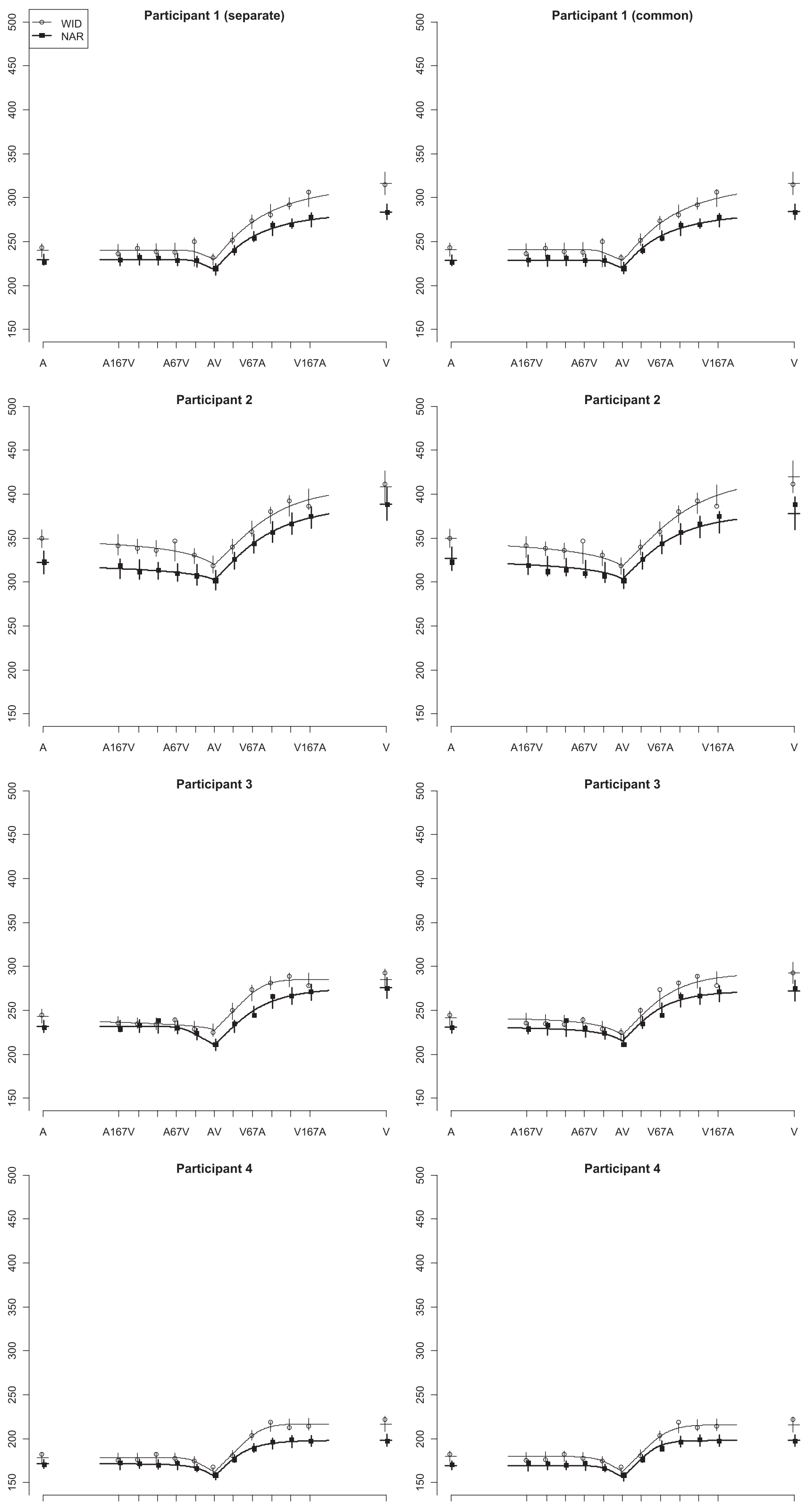

Figure 1. Experiment 1—SOA specific mean response times observed (dots) in the NAR and the WID (central stimuli only). Lines: Model prediction including 95% confidence intervals based on the observed standard deviation. Left: Task-specific models. Right: Common aggregate model with task-specific evidence barrier.

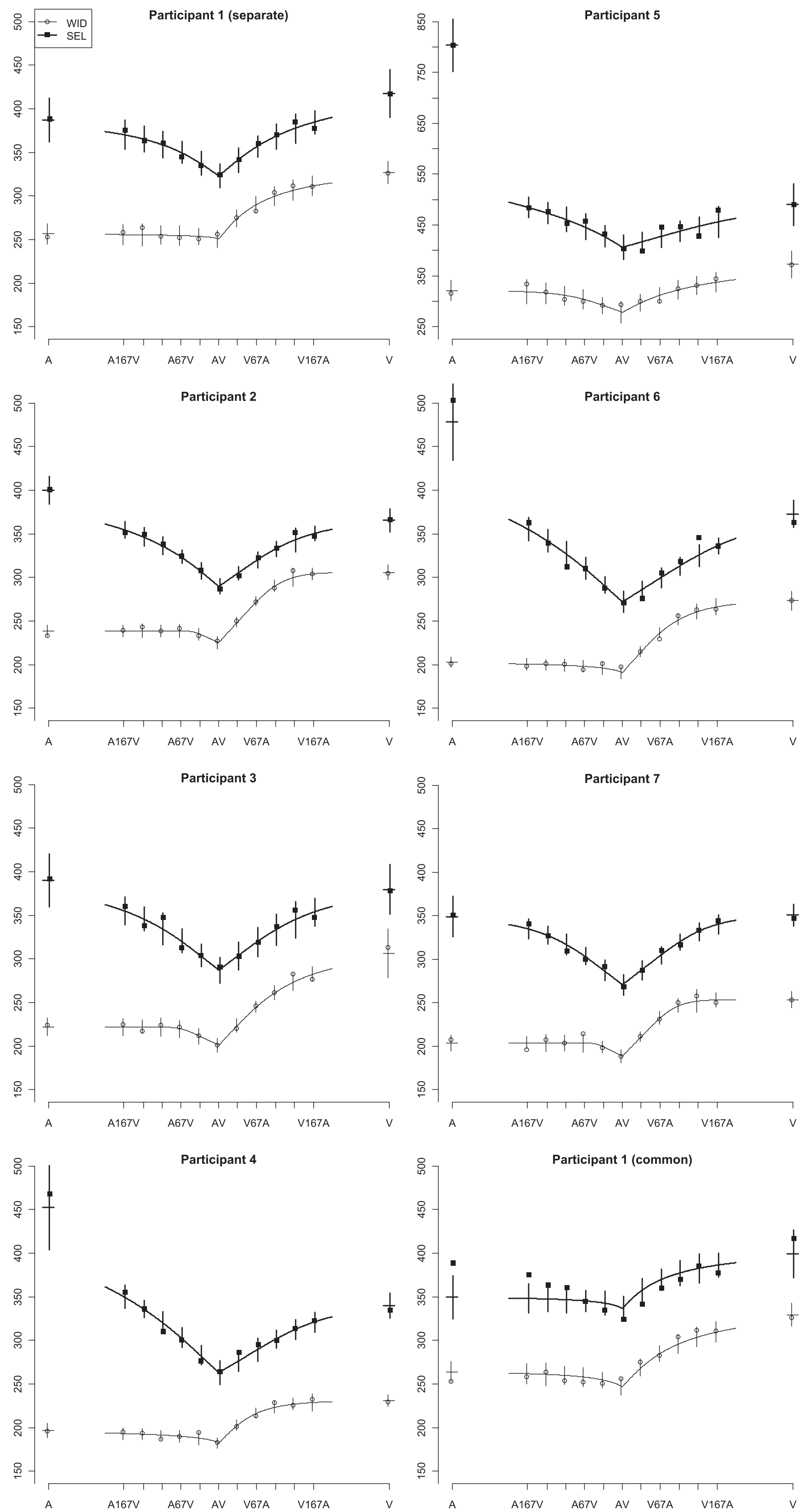

Figure 2. Experiment 2—Separate superposition models for the WID and SEL. A common model cannot be adjusted to the response times observed in the two tasks (lower right).

Table 1
Diffusion Superposition Model for the WID and the NAR, and the Common Model for Both Tasks of Experiment 1

	WID				NAR				Common model			
Participant	1	2	3	4	1	2	3	4	1	2	3	4
μ_V	0.86	0.72	1.14	1.13	0.79	0.57	0.79	1.13	0.83	0.63	0.94	1.13
σ_V^2	71.1	26.9	10.0	10.0	47.5	24.4	25.4	25.3	60.3	23.3	31.9	16.1
μ_A	2.52	1.25	2.16	2.03	1.89	1.19	1.39	1.90	2.22	1.14	1.79	1.98
σ_A^2	10.0	256.4	3157	10.0	10.0	530.3	10.0	37.8	10.0	345.0	209.2	18.5
c_{WID}	(100)	(100)	(100)	(100)	—	—	—	—	(100)	(100)	(100)	(100)
c_{NAR}	—	—	—	—	(73.1)	(73.8)	(81.0)	(77.6)	73.1	73.8	81.0	77.6
μ_M	200.2	268.9	197.2	130.8	190.7	260.3	173.4	130.4	195.6	261.6	185.5	130.7
GOF χ^2	9.00	9.12	11.07	15.73	4.73	0.94	9.52	5.79	15.49	19.91	45.27	25.88
df	8	8	8	8	8	8	8	8	20	20	20	20
p	.343	.333	.197	.046	.785	.999	.301	.670	.748	.463	.001	.170
Summary	$\chi^2_{(32)} = 44.92$, $p = .064$				$\chi^2_{(32)} = 20.98$, $p = .932$				$\chi^2_{(80)} = 106.55$, $p = .025$			

Note. μ_V, σ_V^2 (μ_A, σ_A^2): drift and variance for visual (auditory) diffusion process, *c*: evidence barrier for the WID and the NAR (fixed values in parentheses), μ_M: mean duration of residual component. GOF χ^2, *df*, *p*: goodness-of-fit statistic (significant results indicate bad fit). Summary is based on the sum of the participant-specific GOF statistics.

response times observed in the two tasks. Good agreement between model and data is evident in Figure 1 and Table 1. Replicating earlier results by Schwarz (1994), Diederich (1995), and Gondan et al. (2010), mean response times for asynchronous audiovisual stimuli can be well described by a model assuming linear superposition of channel-specific activity. In simple tasks, multisensory "integration" can thus be reduced to a simplistic additive channel summation mechanism, without necessity of superadditive neural circuitry (e.g., Stanford, Quessy, & Stein, 2005).

In summary, Experiment 1 supports the superposition model for simple responses to audiovisual stimuli for different levels of spatial attention. What then is the role of attention in multisensory integration? Does integration occur in a basic bottom-up manner, or is it necessary to direct spatial attention to the location of the stimuli in order to effectively integrate them (e.g., Feintuch & Cohen, 2002)? We addressed this question by fitting an aggregate superposition model to the response times observed for the central stimuli common to both tasks. Assuming that the stimulus-specific diffusion processes describe elementary perceptual processes common to the two conditions, the diffusion parameters μ_A, σ_A^2, μ_V, σ_V^2, were constrained to be equal in the two tasks. Moreover, as both tasks were simple response tasks (Type A, Donders, 1868/1969), residual processes described by μ_M were assumed to be equal in the two tasks as well. Goodness-of-fit of this aggregate model was acceptable in three participants. Different evidence barriers were allowed in the two tasks: An increased absorbing barrier in the WID, or, equivalently, a reduced criterion in the NAR, reflecting the improvement in stimulus detection when spatial attention is directed to the source of stimulation (e.g., Eimer & Driver, 2000, Figure 1; Hillyard, Hink, Schwent, & Picton, 1973).

In Participant 3, fit of the common model was poor, although the results were qualitatively similar to the other participants. Closer inspection of Figure 1 suggests that in Participant 3, the attentional effect is limited to the visual modality—in the left (auditory) wing of the SOA-mean curve, an attentional effect is virtually absent. In the aggregate model, the barrier *c* corresponds to the evidence criterion common to both modalities. An increased barrier, thus, affects both modalities simultaneously (recall that the mean detection time for auditory and visual stimuli corresponds to c/μ_A and c/μ_V, respectively). This model prediction is in line with the supramodal nature of attentional effects observed in crossmodal attention tasks (e.g., Eimer & Driver, 2000). Participant 3's results are incompatible with this supramodal notion of spatial attention: In this participant, effects of spatial attention were limited to the visual modality only (cf. Driver & Spence, 1998, Box 1).

Experiment 2

In Experiment 2, we introduced a Go/Nogo feature in order to investigate if the superposition model can describe the redundancy gains in selective attention tasks.

Methods

Participants. Seven new students from the University of Regensburg (one male, six female, mean age 24.2 years, one left-handed) participated in Experiment 2. All reported normal hearing and normal or corrected-to-normal visual acuity with an intact field of view. The participants were naive regarding the purpose of the experiment and the stimulus conditions employed. Informed consent was obtained from all participants prior to participation. They received course credit or payment for participation.

Experimental tasks. The apparatus and the stimulus conditions employed were identical to Experiment 1. The simple response task was the same as in the WID of Experiment 1: The participants were told to respond as quickly as possible with their dominant hand to any detected signal at any possible location (left, center, right).

The second task was a selective attention task (SEL): Stimuli were presented, in randomized order, at three locations, but participants were instructed to respond to the central stimuli only (Go trials), and refrain from responding to peripheral stimuli (Nogo).

Procedure. Due to the additional peripheral stimuli in the SEL, the entire experiment prolonged to about 12 hours per participant. Data acquisition was split again into three sessions. In each session, 10 blocks of about 15 min duration were conducted; each block comprised both attentional conditions. Again, the first block served as a training block and the data were not analyzed. Breaks were made on request of the participant. Each of the three locations × SOA stimulus conditions appeared three times within each block, yielding a maximum of 87 replications per experimental condition.

Race model test. For the WID, the race model inequality was tested in the same way as described for Experiment 1. For the SEL, a kill-the-twin correction was applied using the erroneous responses to peripheral stimuli:

$$[F_{V(\tau)A}(t) - F_{v(\tau)a}(t)] \leq [F_V(t) - F_v(t)] + [F_A(t-\tau) - F_a(t-\tau)], \text{ for all } t, \quad (5)$$

with $F_{v(\tau)a}(t) = \max[F_{v(\tau)a}(t|\text{left}), F_{v(\tau)a}(t|\text{right})]$, $F_v(t) = \min[F_v(t|\text{left}), F_v(t|\text{right})]$, $F_a(t) = \min[F_a(t|\text{left}), F_a(t|\text{right})]$ denoting the false alarm distribution recorded for peripheral stimuli presented to the left and to the right location (see Gondan et al., 2010, for a similar procedure).

Superposition model. Again, separate diffusion superposition models were fitted to the mean response times observed in the WID and the SEL. In a second step, we tried to adjust a common model to the two tasks, with identical diffusion parameters describing perception of the same stimuli used in the two tasks, but different evidence barriers c_{WID} and c_{SEL} accounting for different attentional demands in the WID and the SEL. Whereas in Experiment 1, both tasks required simple responses, the SEL task of Experiment 2 requires Go/Nogo discrimination (Type C response, Donders, 1868/1969). This additional requirement was accounted for by allowing different residuals $\mu_{M,WID}$ and $\mu_{M,SEL}$ in the two tasks.

Results

As for Experiment 1, direct comparison of the response times observed in the WID and the SEL is most informative for centrally presented stimuli. Reflecting the increased control demands of the Go/Nogo responses, mean response times for Participants 1, 2, 3, 4, 5, 6, and 7 were substantially higher in the SEL than in the WID (130, 168, 157, 125, 507, 304, and 140 ms, respectively, see Figure 2). The relationship between SOA and mean response time followed the usual wing shape. Omission rate was below 1% in the WID and below 2% in the SEL (Participant 5: 5%). In the SEL, responses to peripheral stimuli occurred in maximally 2% of the stimuli. Misses and false alarms were, thus, not further analyzed (except for the kill-the-twin-correction).

Race model inequality. In the WID, violations of the race model inequality were observed for Participants 2, 3, 4, 6, and 7 (Part. 7: $p = .001$, others $p < .001$), whereas redundancy gains observed for Participants 1 and 5 were consistent with parallel processing ($p = .365$, .111, respectively). In SEL, coactivation effects were observed in all participants (all $p < .01$).

Diffusion superposition model. We first tried to adjust an aggregate model with identical diffusion parameters to the two tasks (Table 2, "Common Model"). The fit of this aggregate model was poor in all participants, and the model systematically underestimated the mean response times for auditory stimuli in the SEL, while auditory response times in the WID were systematically

Table 2
Diffusion Superposition Model for the WID and the SEL, and the Common Model for Both Tasks of Experiment 2

	WID							SEL							Common model						
Participant	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
μ_V	1.04	0.88	0.66	1.33	0.63	0.88	1.04	0.58	0.60	0.53	0.51	0.38	0.41	0.63	0.83	0.83	0.76	1.31	3.14	0.77	1.00
σ^2_V	126.9	10.0	33.2	62.9	94.1	27.5	10.0	59.5	17.1	20.4	10.0	10.0	10.0	10.0	88.4	10.0	10.0	40.7	408.2	33.2	10.0
μ_A	3.80	2.16	1.46	2.42	0.94	2.33	2.14	0.70	0.50	0.50	0.32	0.17	0.29	0.64	1.83	1.30	1.18	1.74	1.69	1.61	1.45
σ^2_A	1997	10.0	10.0	1412	36.5	821.2	10.0	61.1	54.4	28.4	30.6	113.8	34.6	18.4	337.4	10.0	56.1	10.0	8670	157.9	10.0
c_{WID}	(100)	(100)	(100)	(100)	(100)	(100)	(100)	—	—	—	—	—	—	—	(100)	(100)	(100)	(100)	(100)	(100)	(100)
c_{SEL}	—	—	—	—	—	—	—	(100)	(100)	(100)	(100)	(100)	(100)	(100)	75.5	150.1	143.4	215.2	999	78.1	147.1
$\mu_{M,WID}$	230.1	192.4	153.8	155.5	214.5	159.6	156.9	—	—	—	—	—	—	—	209.3	176.3	148.6	144.7	282.1	145.9	145.7
$\mu_{M,SEL}$	—	—	—	—	—	—	—	245.0	198.0	189.6	142.2	223.6	127.6	191.6	308.2	219.2	215.3	192.6	196.8	252.6	211.1
GOF χ^2	7.33	8.35	9.04	9.89	7.84	15.91	12.26	3.85	4.48	7.45	10.57	15.21	25.34	7.18	59.84	252.8	97.17	252.3	70.28	336.7	122.8
df	8	8	8	8	8	8	8	8	8	8	8	8	8	8	19	19	19	19	19	19	19
p	.502	.400	.339	.273	.450	.044	.140	.871	.811	.489	.227	.055	.001	.518	< .001	< .001	< .001	< .001	< .001	< .001	< .001
Summary			$\chi^2_{(56)} = 70.62$, $p = .090$							$\chi^2_{(56)} = 74.08$, $p = .053$							$\chi^2_{(133)} = 1192$, $p < .001$				

Note. μ_V (μ_A), σ^2_V (σ^2_A): drift and variance for visual (auditory) diffusion process, c: evidence barrier for the WID and the SEL (fixed values in parentheses), $\mu_{M,WID}$, $\mu_{M,SEL}$: mean duration of residual component in the WID and the SEL. GOF χ^2, *df*, *p*: Goodness-of-fit statistic (significant results indicate bad fit). Summary is based on participant-specific GOF statistics.

overestimated (summarized goodness-of-fit statistic: $\chi^2 = 1192$, $df = 133$, $p < .001$).

Task-specific diffusion superposition models, however, can describe the mean response times recorded for the two tasks (see Figure 2). Parameters and goodness-of-fit statistics are summarized in Table 2 (columns WID and SEL). The model fit is acceptable for the WID ($\chi^2 = 70.62$, $df = 56$, $p = .090$) and for the SEL ($\chi^2 = 74.08$, $df = 56$, $p = .053$).

Discussion

In Experiment 2, we investigated the role of selective attention in a speeded response task with audiovisual stimuli presented at three different locations. In the first condition (WID), participants had to respond to stimuli presented at any of three locations, whereas in the second condition (SEL) they were asked to respond selectively to stimuli presented at the central location. Thus, the two conditions comprised the same stimulation but required different response types (simple vs. Go/Nogo). As for Experiment 1, response times in the two conditions were compared only for centrally presented stimuli. In line with the increased requirements of the Go/Nogo task, mean reaction times for the SEL were higher compared with the WID. Redundancy gains in the WID significantly violated the race model inequality in only one participant, whereas clear evidence for coactivation was obtained in the SEL.

Task-specific superposition models for the mean reaction times showed an excellent fit for all participants, suggesting that linear superposition of channel specific diffusion processes (Schwarz, 1994) may well explain behavior in simple and more complex response paradigms (Figure 2, left column). Parameter estimates (see Table 2) for task-specific models indicate that selective attention affects both the diffusion and residual processes: (A) In the WID, drift rates turned out to be higher than in the SEL, whereas the mean residual turned out to be lower for the WID than for the SEL. Assuming that the overall response time $\mathbf{T} = \mathbf{D} + \mathbf{M}$ (Luce, 1986, ch. 3) decomposes into perception-related processes $\mathbf{D}$ being described by the diffusion model, whereas $\mathbf{M}$ summarizes everything else (e.g., motor preparation and execution), the manipulation of selective attention affects processing stages related to both $\mathbf{D}$ and $\mathbf{M}$: Increased drift rates estimated for the WID might reflect an increased buildup of evidence in this condition, but can, at the same time, indicate a lower amount of evidence necessary for stimulus detection. The higher μ_M observed in the SEL for Participants 1–5 and 7 is, presumably, due to the increased control demands of the Go/Nogo response selection processes.

The aggregate model incorporates responses of centrally presented stimuli in both tasks; it clearly fails to give a valid description of the mean reaction times in the two tasks. Model fit was poor in all participants ($p < .001$). A single scaling factor c is, thus, insufficient to describe the buildup of evidence under the two attentional conditions. Visual and auditory processing seems to be differentially affected when spatial attention is selectively assigned to one location as compared with the control condition with simple responses. Whereas auditory drift rates are about 2 or even 3 times greater than visual drift rates in the WID task, both drift rates are quite similar in the SEL task. Compared with the simple detection task, location discrimination might be substantially more difficult for auditory compared with visual stimuli. This is reflected by the asymmetric effects of the attentional manipulation on the mean response times (see Figure 2). This differential effect cannot be accounted for by the aggregate model, which assumes that the auditory and the visual channels are both equally affected by the attentional manipulation. Interestingly, the task-specific models show good fit.

General Discussion

The goal of the present study was to investigate effects of different attentional conditions on mean response times in two redundant signals experiments. In Experiment 1 we compared two conditions of narrow and wide spatial attention; in Experiment 2 participants had to attend either selectively to a single spatial location or to three locations simultaneously. Crossmodal attention studies have provided abundant evidence for attentional mechanisms common to vision and audition (e.g., Spence & Driver, 1997) and vision and touch (e.g., Eimer & Driver, 2000), though there seems to exist some degree of independence between the different modalities (Alais et al., 2006).

What effect does attention have on audiovisual integration? While attention seems to be critical for early multisensory event-related potential interactions (Talsma et al., 2007), little is known about the effects of spatial attention on behavior, for example, audiovisual redundancy gains. In all conditions of the present experiments, mean response times were well described by a diffusion model based on linear superposition of modality-specific activation in the two channels (Schwarz, 1994). In Experiment 1, attentional modulation involved a change of the size of the attentional focus and the expected results were obtained. Attention-specific benefits of focused spatial attention were observed (as compared with a control condition with a wide attentional focus); these benefits were well described by a model that asserts different evidence criteria for the two attentional conditions. The lower evidence criterion in the focused attention condition can be interpreted in two ways: On one hand, it might reflect a lower amount of evidence necessary for stimulus detection; on the other hand it might reflect more effective accumulation of evidence in the focused attention condition. The diffusion superposition model is mute in this respect; neurophysiological evidence, however, suggests the latter interpretation (Hillyard et al., 1973; Talsma et al., 2007).

In contrast, in Experiment 2, it was not possible to describe the mean response times in the two attentional conditions by a common aggregate model. The selective attention task of Experiment 2 was, of course, much more complex than the simple response task, involving, for example, suppression of responses to Nogo stimuli. These different response modes (simple response, Go/Nogo response) might be responsible for the failure to predict the mean response times of both tasks in a single, aggregate model (see also Gondan et al., 2010, Exp. 2). Rather, it seems that selective attention differentially affects processing in the two modality-specific channels. It was, however, possible to describe the redundancy gains using task-specific superposition models. This conclusion is supported by the data of all three participants in which modality specific attention effects were observed. To conclude, the same integration mechanism (namely, linear superposition) is involved at different stages of perception.

The spatial Go/Nogo task used in Experiment 2 of the present study differs from the discrimination task used in Gondan et al. (2010, Experiment 2). In Gondan et al. (2010), participants received combinations of audiovisual stimuli (both either targets or distractors). A response was required when either of the stimulus components was a target. For some participants, model fit returned seemingly implausible estimates for some parameters (namely, σ^2_A and σ^2_V were close to zero, suggestive of a deterministic buildup of evidence). It turned out that such a special case of the diffusion superposition model mimics the predictions of a serial self-terminating model of information processing. We argued that these participants might have processed the redundant information serially, as a consequence of response competition induced by combinations of targets in one modality and nontargets in the other modality. In the selective attention task used in the present study, only conflict-free stimulus combinations were used, thereby avoiding response competition effects. The good agreement between model and data (Figure 2, Table 2) demonstrates that the superposition model can actually describe behavior in conflict-free audiovisual redundant signals experiments, even for the more demanding Go/Nogo task.

The two experiments, thus, show that the superposition model (Schwarz, 1989, 1994) can explain redundancy gains under different attentional conditions. Spatial attention, in our experimental setup, could be fully described by a shift of the evidence barrier (which we think is related to more efficient processing in the two sensory channels; Hillyard et al., 1973). Manipulations of selective attention affect the two modalities differentially, but audiovisual integration still follows the principle of linear, additive superposition of modality-specific activation (Stanford et al., 2005; Ma, Beck, Latham, & Pouget, 2006). The present study focuses on basic mechanisms of multisensory integration observable in rather simple experimental tasks. The stimuli used in the present study are, thus, rather abstract and somehow artificial, and we have chosen white noise and Gabor patches mainly because these stimuli are known to be effective in their respective modality (e.g., Watson, Barlow, & Robson, 1983). There is a growing number of studies using the redundant signals paradigm (e.g., about 400 citations of Miller, 1982 in Google Scholar in February, 2011), most of these studies limit their analysis to the test of the race model inequality. If the race model fails, separate activation is ruled out (Miller, 1982). However, without testing a specific coactivation model, little is known about the specific mechanisms underlying the integration of the redundant information. The limited number of studies of formal coactivation models (e.g., Diederich, 1995; Miller & Ulrich, 2003; Schwarz, 1989, 1994) mainly describe redundancy gains observed in simple response tasks with beeps and flashes presented from a single source of stimulation (e.g., the setup used by Miller, 1986). We have shown that for the Go/Nogo task (i.e., a slightly more complex task than just simple responses) coactivation effects cannot be taken for granted and linear superposition does not always describe the observed redundancy gains (Gondan et al., 2010). Although the experimental setup is still far from being ecologically valid, the present study sheds light on the basic principles of multisensory processing and the role of attention therein.

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