

A Computational Approach to Negative Priming

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Priming is characterized by a sensitivity of reaction times to the sequence of stimuli in psychophysical experiments. The reduction of the reaction time observed in positive priming is well-known and experimentally understood [Scarborough et al., 1977]. Negative priming – the opposite effect – is experimentally less tangible [Fox, 1995]. The dependence on subtle parameter changes (such as response-stimulus interval) usually varies. The sensitivity of the negative priming effect bears great potential for applications in research in fields such as memory, selective attention, and aging effects.

We develop and analyze a computational realization, CISAM, of a recent psychological model for action decision making, the ISAM [Kabisch, 2003], which is sensitive to priming conditions. With the dynamical systems approach of the CISAM, we show that a single adaptive threshold mechanism is sufficient to explain both positive and negative priming effects. This is achieved by comparing results obtained by the computational modeling with experimental data from our lab. The implementation provides a rich base from which testable predictions can be derived, e.g. with respect to hitherto untested stimulus-combinations (e.g. single-object trials).

Keywords: Computational psychology; selective attention; negative priming; decision making

1 Introduction

Selective attention to relevant stimuli is often accompanied by active suppression of distracting information. Because effects of this information processing control tend to outlast the duration of stimulus presentation, later sensory processing of the distractor may be influenced. Generally, the repetition of a target stimulus in two successive trials leads to a faster response. This effect is called positive priming. But also the presentation of a previous distractor as a target in a new trial may lead to a deteriorated performance compared to a target which has not been presented immediately before. The behavioral slowdown, called negative priming, is believed to indicate that irrelevant information is not passively ignored, but actively processed. At a later stage, the target has to be favored over the distractor in order to come to a correct response. This mechanism that a distractor is not fully erased from the percept can be seen as the result of evolutionary optimization techniques to improve the accuracy of a response to the target stimulus in human perception.

The prolonged reaction time in trials demanding a response to target stimuli that were previously irrelevant (and hence suppressed) is experimentally penetrable, and therefore the measure of choice in most negative priming experiments. The negative priming effect has been found in a wide variety of experimental contexts and is therefore thought to be a reproducible but sensitive phenomenon (for reviews, see [Fox, 1995, May et al., 1995, Tipper, 2001]). Negative priming experiments are also used in comparison studies to discuss effects of e.g. aging [Titz et al., 2003] or schizophrenia [Kabisch, 2003].

Over the years, various models [Tipper, 1985, Houghton and Tipper, 1998, Neill and Valdes, 1992,

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Milliken et al., 1998] have been developed to explain negative priming effects based on a variety of mechanisms, the most important ones being inhibition and episodic retrieval. However, the available empirical evidence does not clearly favor one model over the others. Some authors have tried to reconcile and integrate the two main classes of models [May et al., 1995, Tipper, 2001]. The dual-mechanism approach to negative priming [May et al., 1995] proposes that inhibition as well as memory retrieval could be the source of negative priming. The experimental context specifies which of the two mechanisms is used. A related account proposes an integrated model [Tipper, 2001], stating that a complete explanation of a complex phenomenon as negative priming must include forward-acting (encoding) and backward-acting (retrieval) processes at the same time. This perspective has so far not been adopted in a model. It provides a source for our present model. The major conceptual framework is however provided by the imago-semantic action model (ISAM) [Kabisch, 2003], whose relevant aspects is described in the following section. A detailed demarkation of the ISAM from the other modeling approaches will be given in the discussion in section 5.

The phenomenon of facilitated response with target repetition is known as *positive priming* [Tipper, 1985]. Although the functional objective of positive and negative priming is not identical, both effects may share similar mechanisms. It is possible that negative priming arises as a trade-off in the process that accounts for faster responses to repeating stimuli. The main goal of this paper is to present both priming effects (as well as several other subtypes) in a combined picture, by means of a formal model. The formalization of the ISAM in the framework of a computational theory serves as a foundation for the derivation of experimentally testable predictions from the computer simulations.

After presenting the conceptual framework in subsection 3.1, we describe the experimental paradigm and briefly review the experimental results in subsection 2.1. Details on the implementation of the model are given in subsection 3.2 and the function and implications of the model are described in sections 4 and 5, respectively.

2 Negative Priming Experiments

2.1 The Paradigm of Negative Priming

In our implementation and the rest of this paper, we always refer to the specific paradigm described in this section. However, negative priming is a universal attribute of human action, and has been shown in many other experiments, adopting all kinds of paradigms (e.g. auditory negative priming [Banks et al., 1995], negative priming in spatial tasks [Milliken et al., 1994]). Although we exclusively refer to identity priming tasks, where the perception of an object is influenced by the perceptual history of that same object, other paradigms such as location priming are not expected to lead to qualitatively different results, cf. [Kabisch, 2003]. Since negative priming tends to disappear with problem complexity, identity priming is an option that minimizes task complexity. The decisive feature in the experiments reported here is color, i.e. targets and distractors are shown as invariable in their respective color.

Because four objects occur in pairs during the prime and the probe displays respectively, the two simultaneously presented objects never being the same, seven relevant combinations of target and distractor relations are conceivable. We further exclude the two conditions in which the target is new in the probe display but the distractor object of the probe display had already been shown as a target or as a distractor in the prime display. The role of these stimulus combinations is still unclear and the effects do not as yet bear any significance. The five conditions which remain are summarized and labeled in table 1. The important negative priming condition, where the former distractor becomes the new target, is labeled NP. If in addition the former target becomes the new distractor, we speak of added negative priming and label it as NP2. The condition for positive priming (PP) is the repetition of the target. If in addition the distractor is also repeated, we call this added positive priming (PP2). All reaction times are compared with the control condition (CO), where two stimuli, which have not been displayed in the prime display, are shown in the probe.

The experimental setup for the paradigm described above is shown in Fig. 1. The subject is presented with a display, where two overlapping stimuli in distinct colors are arranged in slightly shifted positions. The color determines the function of the respective object as a target or distractor: Green stimuli are

Table 1. Regular priming conditions.

condition	prime display		probe display		
	target	distractor	target	distractor	
NP	A	B	B	C	distractor(n) = target($n + 1$)
NP2	A	B	B	A	target \leftrightarrow distractor
PP	A	B	A	C	target(n) = target($n + 1$)
PP2	A	B	A	B	target, distractor remain the same
control	A	B	C	D	None of the above match

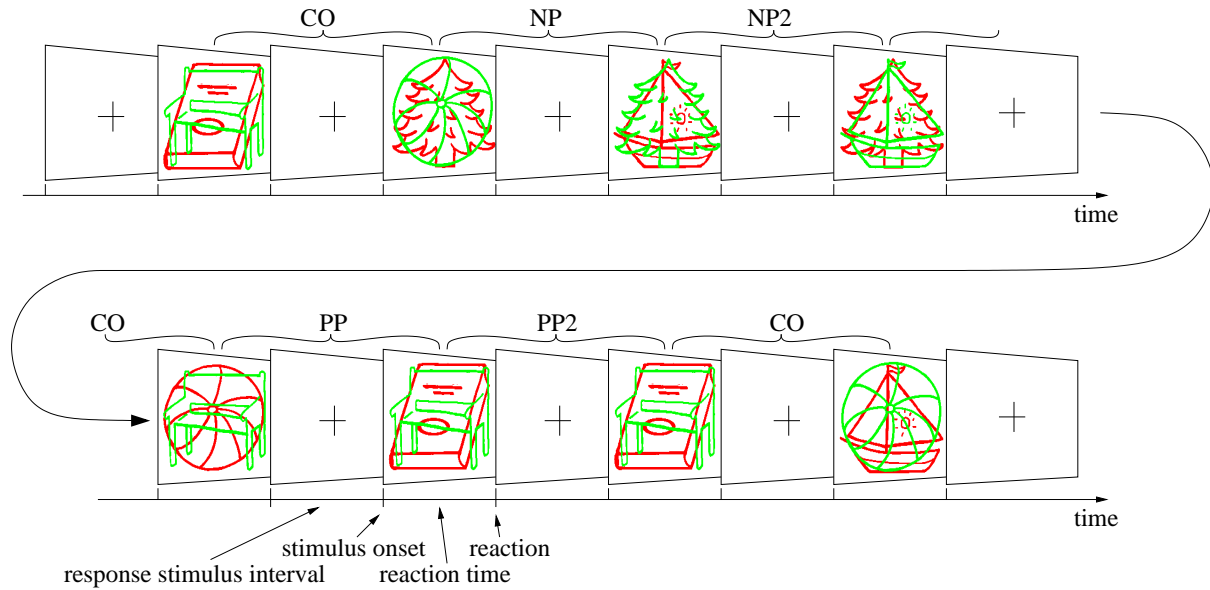


Figure 1. Example of a sequence of stimuli used in the experiments like [Titz et al., 2003]. Consecutive screens are shown. Either stimuli or a fixation cross is displayed. The meaning of the acronyms introduced in section 2.1 is explained. E.g. in the sequence of the second and third stimuli, the tree switches from distractor to target. We therefore have a negative priming condition. As the target of the second stimulus is a ball but the distractor of the third screen is a boat, we do not have the NP2 condition but a simple negative priming.

targets and the red ones serve as distractors. The subject is instructed to name the green object as soon as he is sure about its identity. Then, after the presentation of a fixation cross, the next display is presented.

In our experiments we use voice recording together with a sound level threshold to determine the reaction time for every trial. For a sharper onset of the sound signal, stimuli which begin with a plosive were chosen. To minimize side effects of memory and the probability of false answers, only a small number of stimuli (5 to 10) is used and the subjects are trained to recognize them before the experiment. The stimuli are designed for comparability, i.e. the area covered by the object being constant over all stimuli and the number of line crossings and relative complexity of the stimuli being approximately the same. Care was taken in preceding studies to select and tweak the stimuli for good perceptibility and recognizability.

Because the interval between successive displays is known to be a crucial variable [Kabisch, 2003], we vary the response-stimulus interval (RSI) in our experiments rather than an inter-stimulus interval (ISI).

2.2 Experimental Method

In order to compare the ISAM with concrete data of a negative priming experiment, we briefly describe an experiment in this section together with the results in section 2.3.

Participants: Participants were 12 adults (undergraduate students from the University of Göttingen, Germany; 4 male and 8 female; mean age 23.6 years, SD = 4.6). All participants received course credit or were paid 8 € for taking part in the study.

Design: The effects of object and response relation were studied in a design with priming conditions as a repeated measures factor. The priming conditions were the control condition (CO), the negative priming condition (NP), the negative priming condition with a switch of target and distractor (NP2), the positive priming condition (PP) and also the positive priming condition with a repetition of target and distractor

(PP2) as described in section 2.1 above.

Materials and Apparatus: The displays consist of superimposed line-drawings of five green target- and red distractor-objects (red-green-blue coordinates were (0, 255, 0) for green; and (255, 0, 0) for red pictures). The figures had approximately the size of 6 cm × 7 cm when displayed on the screen. To minimize biases in naming latencies between stimuli that could have originated from a delayed triggering of the microphone, the objects all began with the same initial plosive letter. The objects were: ball (Ball), tree (Baum), bench (Bank), boat (Boot), bed (Bett).

The task administration was done by computer using Presentation Software (Version 9.20). The displays were presented in the middle of a 19" SVGA monitor connected to an IBM-compatible computer. The participants sat in front of the monitor at a distance of approximately 80 cm. Each stimulus covered a visual angle of 5.0° and 4.3° vertically. Therefore stimuli appeared in the focal area.

The participants had to process a series of successive presented displays. The previously processed display ($n - 1$) is called the prime and the actual display is called the probe. Before processing 420 experimental trials in 10 blocks of 42 trials all participants processed 20 practice trials. Overall 400 trials were analyzed (80 trials of each priming condition), while the first two start trials of every block were excluded from analysis. Object presentation was evenly assigned to the different priming conditions and the appearance as target and distractor.

Procedure: All participants were tested individually in sessions that lasted no longer than 70 minutes. Before the start of the experiment, color discrimination was tested and subjects had to finish a memory span task.

At the beginning of the experiment, line-drawings of stimulus objects were shown to the participants printed in black along with their names. The participants were told that they would see these objects as overlapping pictures; one drawn in green and one in red. Subjects were instructed to name the target-objects aloud and ignore the superimposed red objects. They were told to answer as quickly and as accurately as possible.

To familiarize participants with the experimental demands, 20 practice trials preceded the actual recorded trials. Subjects started each sub-block by pressing the space bar, thereby self-determining the length of the break. Each block of the experiment comprises 42 trials. Each trial consisted of the following displays: (a) a fixation cross, centered on the screen for 500 ms; (b) a display containing superimposed pictures shown to the response, but not longer than 2 seconds; (c) a blank screen for 1000 ms. The length of the current RSI was therefore 1500 ms.

An error was registered when subjects named the distractor, used a wrong name, stuttered, or failed to answer. Once the participants had completed all the tasks they were each asked whether they had any trouble in dealing with the experimental setting, e.g. difficulty in identifying the presented pictures.

2.3 Experimental Results

The mean reaction time depending on the priming condition, standard deviations, and the effect strength, i.e. the deviation from CO-trials, are reported in Table 2. Erroneous trials (2.4%) were not considered in the analysis. Trials with response latencies less than 250 ms or more than two standard deviations above the individual mean of each priming condition were excluded as outliers (4.7%). The NP2-trials produce the slowest response, followed by NP- and CO-trials, whereas the response to PP-trials was faster and the PP2-trials produce the fastest response compared to control trials.

A one-way analysis of variance (ANOVA) was used to explore effects of the five different object repetition (priming) conditions (CO, NP, NP2, PP, PP2). The alpha level for all analyses was set at .05. Greenhouse-Geisser corrected degrees of freedom were used as the data violated the assumption of sphericity. Reaction times depend significantly on the priming condition $F(1.45, 15.93) = 23.27$, $MSE = 1938.83$, $p < .001$. Planned comparisons showed that reaction times in NP- and NP2-trials were significantly increased, as compared to CO-trials (CO vs. NP: $t(11) = -3, 57$, $p < .004$; CO vs. NP2: $t(11) = -3, 37$, $p < .006$). As anticipated, the reaction time for trials in the attended repetition conditions PP and PP2 were significantly decreased (CO vs. PP: $t(11) = 3, 11$, $p < .01$; CO vs. PP2: $t(11) = 4, 74$, $p < .001$). The directed comparison of attended repetition conditions reveal a difference of reaction time (PP vs. PP2: $t(11) = 6, 11$, $p < .001$),

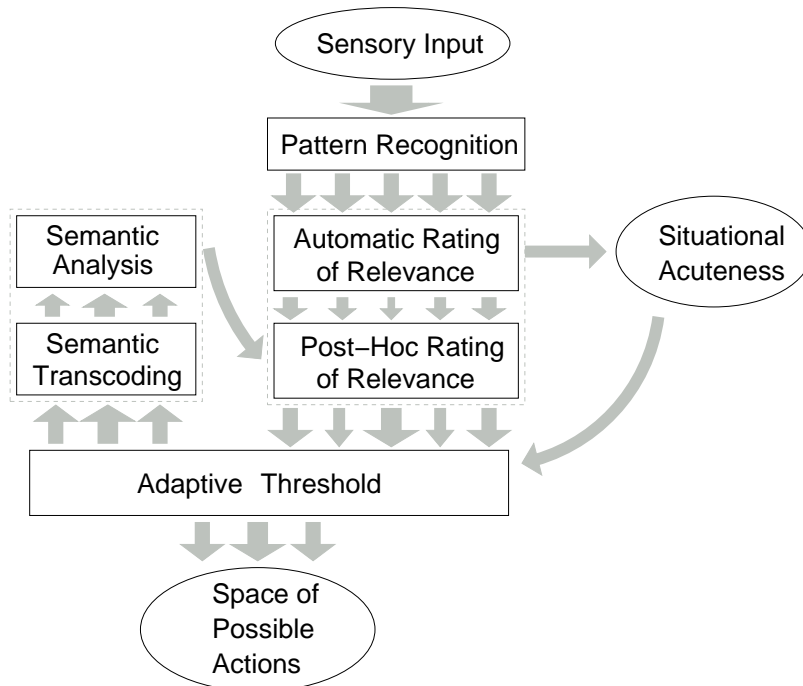


Figure 2. Schematic view of the ISAM. The right dashed box represents the preliminary rating of relevance for the perceived objects. The direct relevance of certain objects drives the factor of situational acuteness that controls speed and accuracy of the computation. The level of global activity affects a threshold which truncates the list of perceived objects into a space of possible actions. A decision is achieved if in the set of applicable actions only a single one is left. The dashed box on the left contains a semantic analysis of the perceived objects. It is able to project back to the posterior rating of relevance in a so-called "semantic feedback loop". The interaction among the components leads to a decision about a reaction by a dynamical process.

whereas the reaction time of ignored repetition conditions did not differ (NP vs. NP2: $t(11) = -0,60$, $p = .558$).

Table 2. Reaction times for a response stimulus interval of 1500ms.

condition	control	NP	NP2	PP	PP2
mean reaction time	660.22	681.57	685.92	625.02	600.69
effect	—	21.36	25.70	-35.20	-59.53
standard deviation of rt	62.85	69.65	78.04	65.29	70.56

3 Model and Implementation

3.1 The *imago-semantic action model*

In the discussion of the experiments we refer to the conceptual framework of the imago-semantic action model (ISAM) [Kabisch, 2003] since its conceptual consistency and definiteness allows for a straightforward and non-arbitrary computational implementation. For conceptual clarity, we will refer to the computational implementation of the ISAM as CISAM which, as a concretion of the model, adds some assumptions in addition.

Both ISAM and CISAM differ from other models, such as [Tipper, 1985], by postulating only one effective mechanism for the emergence of both positive and negative priming effects. This mechanism comprises the adaptation of a threshold to the global mean activity level, acting in the same way for different stimuli, cf. Fig. 2. The original model is intended to provide a general description of decision-making and is mainly restricted to humans, due to its incorporation of certain aspects of language.

In the model, the process of low-level perception and pattern recognition is abstracted, i.e. the presented objects are assumed to undergo a pre-attentive processing and perception stage, resulting in an abstract cognitive representation of the objects. This assumption is not severe, considering the simplicity of the

stimulus set, cf. Fig. 1. On this abstract level, it is possible to control perceptual accuracy and speed by means of an acuteness variable which is based on the situational context. The model mainly focuses on the decision between targets and distractors. Formally, the decision is determined by the task instruction, which is made accessible to the model via the semantic loop (left in Fig. 2). In contrast to the abstracted early visual processes, the decision is supervised by attention and a conscious application of the task instruction.

Initially the stimuli are assumed to be processed automatically according to a relevance rating based on low-level features such as motion or color. The stimuli are sorted hierarchically by their (automatically assigned) relevancy. Every stimulus is accompanied by an action incentive. The relation between stimulus and associated action is that strong that we will speak of the action incentive and the perceived stimulus synonymously. The subject has to decide which one of the actual action incentives to follow, but we will refer to this as a decision between the different stimuli.

Attention is modeled as a truncation of the perceived stimulus set by a threshold which is assumed to be controlled by activity in the anterior cingulate cortex, which is identified by fMRI studies to account for action decision [Winterer et al., 2002]. Besides these findings, the model does not claim a neuronal equivalent for every unit. In concrete modeling terms, the threshold increases with growing overall activity, i.e. if more than one option for action exists, the threshold further increases, thus limiting the number of remaining options above threshold. Therefore the stimulus relevancy does not need to be fixed beforehand. Note that the acuteness variable only influences the speed of the decision via the adaptation rate of the threshold, but does not influence the decision itself. Focusing on the priming-based differences in reaction times, the experimental paradigm is chosen such that the acuteness level can be assumed to be constant across all trials. Therefore we exclude this aspect of the ISAM in the present implementation.

Up to this point, the model describes the forward acting selection process with respect to present stimuli, as it may happen in all higher animals [Mesulam, 1998]. In addition to this, humans are capable of reflecting upon the automatic order of relevance and consciously assigning modified relevancy values to the respective objects. According to the dual-code hypothesis (cf. [Krause et al., 1997]), this happens in a semantic space where stimuli are processed jointly with the implied actions. The relevance of certain stimuli can be changed in a posterior rating of relevance in this semantic space, which takes into account all the available information and affects the adaptation process of the threshold by a feedback mechanism. These backward acting processes control the way perceptual input is classified, thus possibly achieving a reordering of the original hierarchy. The activation corresponding to a target is typically amplified (due to its nature of being a "target") such that even if the primary features (as is the case in our experiments, cf. 2.1) imply the contrary, the target-related activation eventually becomes significantly stronger than that of any distractor.

In contrast to the ISAM, a few dynamical properties have been adjusted in the computational implementation (CISAM). Whereas ISAM usually assumes linear changes in the variables, the CISAM instead uses linear differential equations that cause an exponential saturation, which suffices for the relevant range of response-stimulus intervals (cf. 3.2).

The computational formulation of the model requires the specification of the space of object representation, such that at least a metric in this space is given. This problem is circumvented here by a stimulus set which is chosen to be approximately equidistant in the semantic space such that a zero-one metric is sufficiently specific. Here, stimuli are either maximally different or identical, and priming effects will be measurable only if the same object is presented in subsequent trials.

3.2 Computational formulation of the ISAM

The simulations essentially follow the paradigm which we introduced in the previous section. We consider a set of n stimuli which were trained in advance. Each stimulus is represented by the activation of a detector function which models a cell assembly that represents the stimulus. In addition to the stimulus-driven activation, the detector is subject to intrinsic dynamics.

Since the stimuli can occur either as a target or as a distractor, each is coded by two variables. One, x_i^τ indicates the presence of a stimulus $i \in \{1, \dots, n\}$ as the target object, while x_i^δ codes the activity of

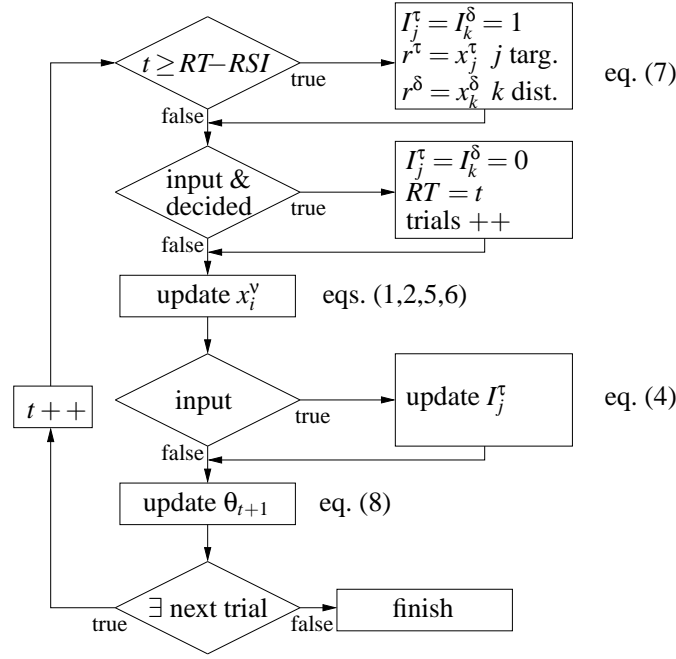


Figure 3. Schematic view of the loop structure of CISAM. Discrete time is denoted by t . Reaction time and response stimulus interval in the discrete time units are labeled by RT and RSI respectively. It is assumed that stimulus index j is the present target and k indicates the distractor of the current trial.

the distracting stimulus. x_i^τ and x_i^δ are assumed to represent feature combinations which are considered to precede an object representation (see e.g. [Schrobsdorff et al., 2007] how such feature combinations can be combined with an object representation). The system is modeled by a set of differential equations which determine the time course of the unit activations and of the common threshold variable. Stimulus input is presented to the model in the form of jumps in the fixed points of the activation variables, i.e. they are modeled as delta-pulses to be integrated by the internal units (3), (4). The integration in the neural units is modulated by a temporal convolution with the time constants α and β in the following way: The activity x_i^ν , where $\nu \in \{\tau, \delta\}$ denotes target or distractor respectively, rises exponentially with time-constant α to a certain level I_i^ν , which is determined by the input.

$$\frac{1}{\alpha} \frac{dx_i^\nu}{dt} = I_i^\nu - x_i^\nu \quad \text{if } x_i^\nu < I_i^\nu \quad (1)$$

If the input is switched off the population activity exponentially decays towards zero. If the present input is lower than the population activity it tends towards this input (2). In both cases the decay constant is β .

$$\frac{1}{\beta} \frac{dx_i^\nu}{dt} = I_i^\nu - x_i^\nu \quad \text{if } x_i^\nu > I_i^\nu \quad (2)$$

We assume an abstract recognition mechanism that activates stimulus-specific units. Inputs are represented by an activity level of one unity in the presence of an input or otherwise by zero activity (3), (4). The semantic feedback loop amplifies the activity of the unit representing the target I_i^τ linearly with feedback strength ξ (4).

$$I_i^\delta = \begin{cases} 1 & \text{during presentation of object } i \text{ as distractor} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$I_i^\tau = \begin{cases} 1 + \xi \Delta t & \text{during presentation of object } i \text{ as target} \\ \Delta t & \text{\(\Delta t\) denotes the elapsed time while stimulus onset.} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

As x_i^τ and x_i^δ belong to the same object i , they interfere. This interference is given by a negative interaction. One and the same object cannot be target and distractor at the same time. Therefore these variables cause conflicts with the strength of the symmetric negative interference ζ during simultaneous activation. Assuming the absence of input, Eq. 2 becomes (5) or (6), respectively.

$$\frac{1}{\beta} \frac{dx_i^\tau}{dt} = -x_i^\tau - \zeta x_i^\delta \quad (5)$$

and vice versa

$$\frac{1}{\beta} \frac{dx_i^\delta}{dt} = -x_i^\delta - \zeta x_i^\tau. \quad (6)$$

The core of the model is the adaptation of the threshold. The threshold θ (7) is driven by the average activity \bar{x} (8). The parameter γ denotes an adaptation constant and Δ is a delay time. This is a standard version of a winner-takes-all mechanism.

$$\frac{1}{\gamma} \frac{d\theta}{dt} = \bar{x}(t - \Delta) - \theta \quad (7)$$

The average activity depends on the object representations x_i and also on two memory variables: r^τ and r^δ , which are residual activities from previous activations in the present target and distractor, respectively.

$$\bar{x} = \frac{1}{2} \left(r^\tau + r^\delta + \sum_{i=1}^n (x_i^\tau + x_i^\delta) \right) \quad (8)$$

At the moment of input onset, r^τ and r^δ are set to the activity level of the appearing target and distractor. If the new display contains stimulus j as target and k as a distractor, then we set the following at the point of stimulus onset:

$$r^\tau = x_j^\tau, \quad r^\delta = x_k^\delta \quad (9)$$

The variables r^τ and r^δ form a separate temporary representation of the current objects, which undergoes a different time course after initialization.

The decision about the target object is performed globally. We test whether exactly one variable is activated above threshold level θ . This test is additionally conditioned due to the fact that the threshold is higher than a fixed sensitivity level σ . We thus avoid decisions without a significant activation, e.g. when the adaptive threshold θ is near zero. All variables that form the model are presented in a joint plot in Fig. 4, for details cf. the insets. Most activity variables x (green for x^τ , red for x^δ , in different textures for the different objects i) are effectively zero. Only the variables that are or had just been subject to input have a significant activity. The threshold θ (blue) is oriented along the average activity level \bar{x} (dash-dotted blue).

Parameter values are chosen following several principles. Freely scalable parameters such as distractor input I_i^δ , are chosen such that they are kept as simple as possible. Certain bounds have to be respected,

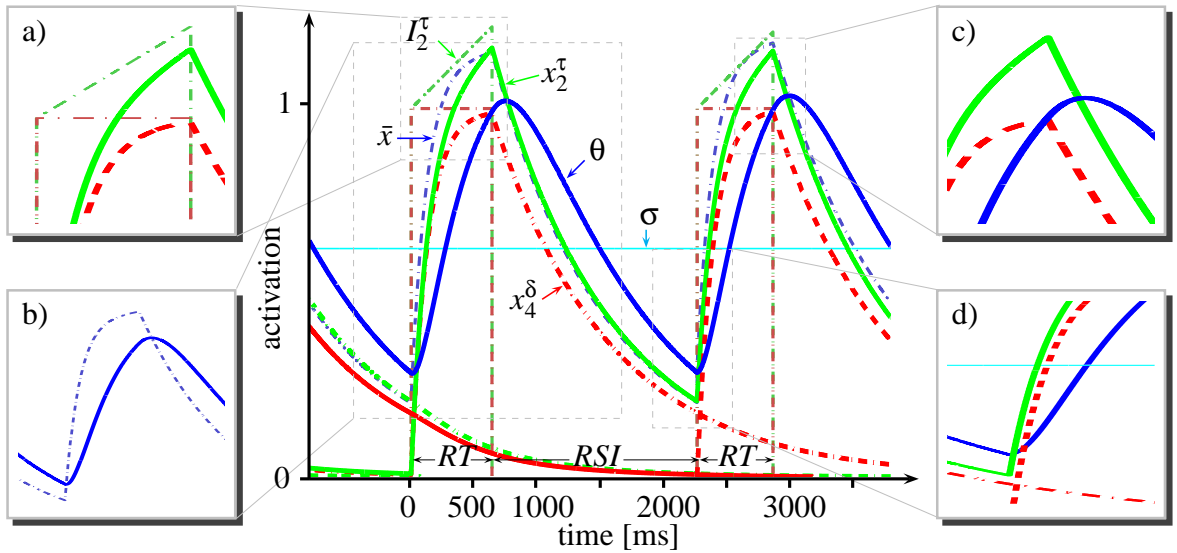


Figure 4. Activity vs. time. All traces relevant to the model are shown. Distractor x_4^δ activation is red and target x_2^τ activation green, the threshold level θ is blue. Additionally, the average activity \bar{x} is plotted in dash-dotted blue, the absolute sensitivity level σ in cyan. The inputs together with the semantic amplification are shown as a thin dash-dotted pattern. Their color corresponds to their role as target or distractor input. Insets: **a)** The activation curve of target and distractor approach their input exponentially. The input of the distractor is fixed to one. The input of the target is linearly amplified by the semantic feedback loop. **b)** The exponential approach of θ towards the global average \bar{x} is delayed by a certain time interval. **c)** At the moment when θ crosses the distractor activity only the target activation is above θ , and a decision can be made. **d)** During the fast rise of the activation of the new stimuli there is a short time interval where also only one activation surpasses θ . Due to the global sensitivity level σ , no decision is provoked.

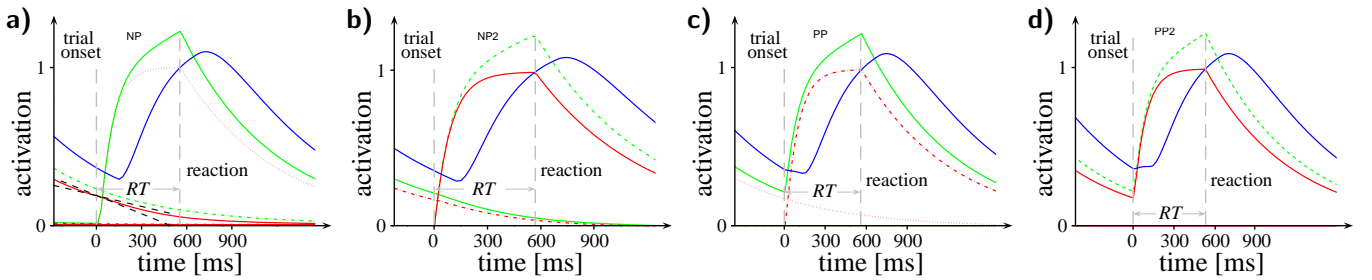


Figure 5. Time evolutions of the activation variables during one simulated trial. Only the activation of objects presented in the current trial or the preceding prime trial are visible, the other eight activation variables are virtually zero. **a)** NP condition. The forced decay of activity of the former distractor variable x_4^δ , where x_2^τ is the target in the second trial, is visible in a subtle kink that is pointed up by two black dashed tangential lines. These tangentials are not drawn in subplot b) for comparison. **b)** NP2 condition. Kinks are present in both the former target and distractor, as they are influenced by the rising activation of the new target and distractor. **c)** PP condition. The activation of the target, which is the same object as the previous target, rises from a certain level above baseline, as it has not yet decayed to zero when the new input is switched on. The activation approaches the input from this step. This shortens the reaction time significantly. **d)** PP2 condition. Here, both stimuli stay the same and they both approach their input from a higher level, which shortens the reaction time even further.

e.g. the sign is usually predetermined, but also the order of depending variables is fixed. The tuning of the model should be subject to an intense parameter scan in order to find different dynamical regimes. However this has to be postponed to later research. Here, the fine tuning is done by intuition.

4 Computational Results

4.1 Comparison to the experimental data

Fig. 5 shows the time series of a trial in the simulated model. The four sub figures refer to the four main cases (NP, NP2, PP, PP2) which were described in section 2.1. Since the scale of time is a degree of freedom in the simulation, we performed a temporal gauge to match the average reaction time in the control trials.

In the NP-trial in Fig. 5a, the activation of target and distractor from the prime stimulus decay with a characteristic exponential profile (2). The threshold θ follows these activations. At time $t_0 = 0\text{ms}$ the RSI has elapsed and a new stimulus is shown. This drives the activations x_j^τ and x_i^δ of the new target and distractor (respectively) exponentially towards the input level $I_i^\delta = 1$ and $I_j^\tau = 1 + \xi(t - t_0)$. At time t_0 , these inputs are similar. Later the difference between the activations increases. At $t = 565\text{ms}$ the threshold θ follows with a delay t_{delay} . It approaches x_i^δ , which has meanwhile arrived close to I_i^δ . If the activity of the distractor is surpassed by the adaptive threshold, then the distractor is cut out of the space of possible actions. Thus, an unambiguous decision in favor of the target can be made.

Now, the display presents a fixation cross, i.e. the inputs I_i^δ and I_j^τ are switched off and the activations x_i^δ , x_j^τ and θ decay correspondingly. The characteristic time course in a NP-trial shows a kink in the activation of the distractor variable x_j^δ when the distractor becomes the target. Via the coupling strength ζ , the rise of x_j^τ causes an acceleration of the decay of the activation and, consequently, a slower rise of θ . The threshold reaches x_i^δ later than in a control trial. In the NP2-trial (Fig. 5b) the two decaying activations from the previous stimulus are decaying faster. The overall activity is thus even lower and the adaptation of θ is more strongly slowed down, such that the response is even slower in NP2-trials.

In the positive priming condition on the other hand (Fig. 5c) the same variable x_j^τ is activated again by input and therefore starts off at t_0 at a higher level of activation compared to a control trial. As discussed in section 3.2 the residual activity of x_j^τ before stimulus onset is stored in the appropriate variable r^τ , which is subject to an intrinsic decay, and adds to the overall activation level \bar{x} that drives θ . The augmented activity level of x_j^τ at the beginning of input causes a higher \bar{x} that shortens the time that θ needs to reach x_i^δ significantly. Therefore the reaction time is reduced in comparison to the control trials. In the PP2-trial (Fig. 5d), the reaction is even faster due to the departure of both target and distractor activations from a higher level of remaining activity.

We simulate sequences of 400 trials. The results from the simulations show a close correspondence to the results we obtain in our experimental studies. The results of a simulated session are presented in table 3. We thus added 200ms to all of the reaction times in order to account for perception and action initiation processes which are not covered by the CISAM.

Table 3. Reaction times for a response stimulus interval of 1500ms. To match the experimental data given in 2.3 an additional delay of $\approx 135\text{ms}$ for perception and action initiation has to be assumed. These processes will also further raise the variance but not alter the strength of the effects. Given are also the variance and the effect in dependence on the condition. These reaction times were obtained in an exemplary simulated session of 400 trials. The parameters of this simulated experiment were: $\alpha = 0.028$, $\beta = 0.003$, $\xi = 0.0016$, $\zeta = 0.0053$, $\gamma = 0.013$, $t_{delay} = 15\text{ms}$ and $\sigma = 0.62$. A simulated time step was 0.3ms .

condition	control	NP	NP2	PP	PP2
mean reaction time	525.84	546.40	552.12	489.76	465.56
effect	—	20.55	26.28	-36.09	-60.29
variance of rt	14.78	19.62	22.19	18.38	17.31

4.2 Dependence on the response stimulus interval

An interesting aspect for the evaluation of the model is the dependency of priming effects on the response-stimulus interval (RSI). The adaptation of the threshold critically depends on the length of the RSI. This is due to an adaptation to the specificity of the stored information rather than the exact average level of activation. In the computational model, this corresponds to a weighting of the averaged activity in the process of the adaptation of the threshold. We simulate the state of the model system during medium RSI from about 1s to 2.5s. Both very short (below one second) and very long RSI (on the order of hours or more) are not covered by the model and are discussed in section 5. In the first case, the perception process needs to be specified in more detail, which would lead to a stronger dependency of the model on the particular experimental setup. In the latter case, we would need to extend the model with specific memory mechanisms which is beyond the scope of the present approach.

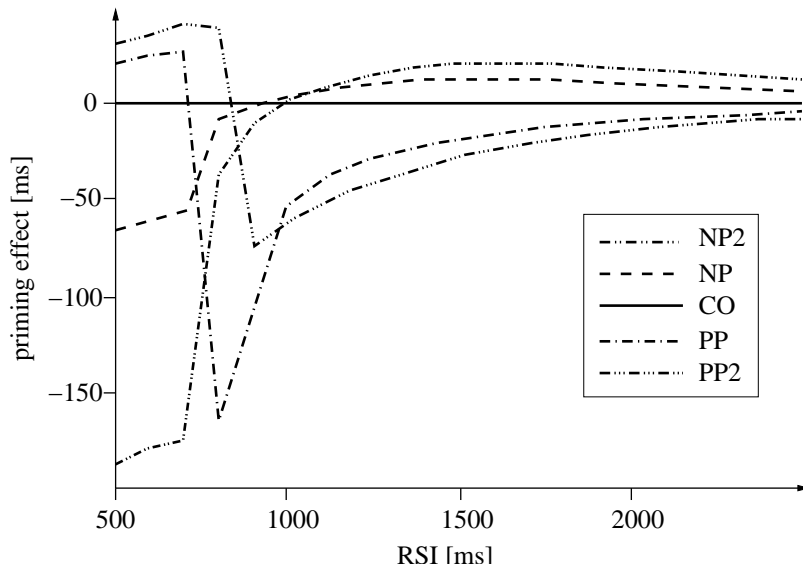


Figure 6. Differences in the reaction times for the four main stimulus conditions in dependence on the response-stimulus interval.

It is a known fact that reaction times in human subjects are strongly affected by the RSI [Kabisch, 2003]. At very short RSI for example, a PP trial is paradoxically slower than baseline and in medium RSI the priming effect in NP2-trials is weaker than in simple NP-trials. The occurrence of these so-called paradoxical effects in experimental studies [Kabisch, 2003] for very short RSI is confirmed by the computational model, cf. Fig. 6. In the model some of these results are due to a backward threshold crossing by the activation variables.

4.3 Variation of distractor saliency

One of the characteristics of the negative priming phenomenon is the influence of distractor saliency on negative priming. The empirical finding, that the negative priming effect increases with growing saliency of the distractors is generally labeled reactive inhibition (e.g. [Grison and Strayer, 2001, Houghton et al., 1996, Lavie and Fox, 2000, Tipper et al., 2002]).

In two experiments Grison and Strayer [Grison and Strayer, 2001] manipulated the perceptual quality of the target or the distractor. Their data indicates that negative priming is dependent on the activation of postperceptual representations of the distractor. Thus a more salient postperceptual distractor representation leads to a stronger negative priming effect. They found stronger negative priming and weaker positive priming for a degraded target compared to a degraded distractor. This relation was predicted by the inhibition model [Houghton et al., 1996] and could be confirmed by [Tipper et al., 2002].

The question how distractor saliency affects reaction times in terms of the CISAM is not easily answered as reaction times depend on the sensitive interplay of all parts of the model. The saliency of the distractor can be altered by changing equation (3) such that in the presence of a distractor stimulus the distractor input I_i^{δ} equals the saliency s . It denotes the saliency relative to the target input. Equation (4) which describes the target input I_i^T stays unchanged. Fig. 7 shows the reaction times produced by the CISAM if the distractor saliency s is changed from 1 (equal distractor and target saliency) to 1.25 (distractor saliency 25% stronger than target saliency).

The CISAM shows several effects when exposed to distractors of varying saliency. Generally, a stronger distractor saliency leads to longer reaction times. More time is needed to blank out the distractor to be able to respond to the target. Computationally this is due to the higher level, the threshold has to reach in order to cut out the distractor activation from the space of possible actions. Counteracting is the fact that the residual activations from the former trial are still higher, due to the higher level of target and distractor activation at the point of the prime decision. This contributes to a higher threshold level at trial onset, thereby accelerating an answer. But this effect is weaker than the influence of a higher distractor

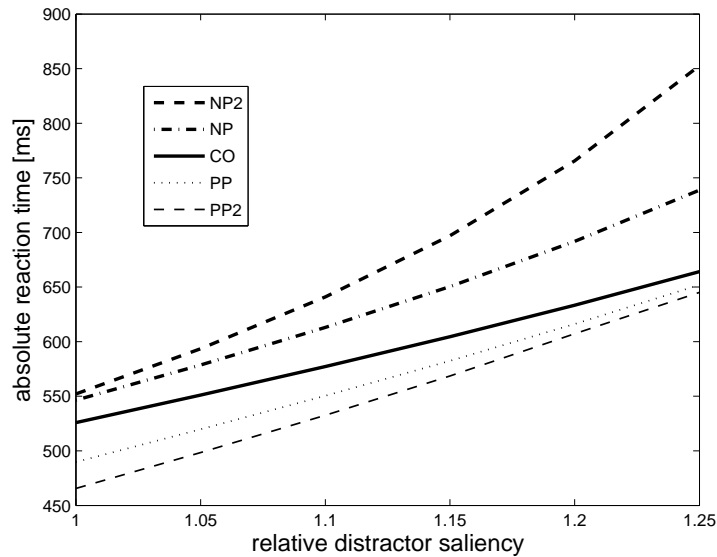


Figure 7. Differences in the reaction times for the four main stimulus conditions in dependence on the relative distractor saliency.

activation level the threshold has to reach for a decision.

The two positive priming effects PP and PP2 become weaker with growing distractor saliency. The reason for this is the exponential dynamics of the activation variable. Positive priming is produced by greater residual activation of the target variable compared to a control trial. This activation difference between positive priming and control decays also exponentially. Thereby longer reaction times and thus a higher distractor saliency reduce positive priming effects exponentially in the framework of the ISAM.

Both negative priming effects grow with higher distractor saliency. Negative priming is produced by an interference between the former distractor activation and the new target activation accelerating their decay reciprocal. With higher distractor saliency more activation from the prime trial carries over. The interference in (5) is dependent on the former distractor activation. Therefore a stronger activation leads to a stronger interference and thus to a bigger NP effect.

4.4 Predictions for single-object trials

The present model is critically tested by the application of single stimuli during the course of the experiment. In single-object (SO) trials only a single object is presented. With respect to the experimental setting, it is only conceivable to use single-object trials with the object being a target. If single distractors were to be included, a no-response answer would be necessary, disturbing the flow of the experiment. Nevertheless, the implementation of the CISAM enables us to predict reaction times in these conditions. A non-reaction is possible at the moment, when the distractor activation reaches a strength that would lead to the classification of a target.

We introduce a number of new categories in addition to the ones named in section 2.1. SO-trials occur in three variants, realizing special cases of the standard conditions NP, PP and CO relative to the preceding target/distractor pair (see upper half of table 4). We are also aware of numerical effects in the reaction times of the CISAM of preceding SO-trials to standard trials. Therefore we further separate these three trial conditions from trials which were preceded by both target and distractor. In our notation, four letter abbreviations denote the six new conditions: If the preceding display contained a single stimulus, the first two letters are SO, and the last two letters indicate the condition of the actual display. If the present trial shows only a single object, the first two letters denote the condition it matches in relation to the preceding display. Cf. table 4 for the appropriate naming of the resulting additional cases.

When SO-trials are presented to the model, a dramatic reduction in reaction time is observed, as shown in table 5. Columns 2 – 4 contain much smaller values than expected in trials with two simultaneous

Table 4. New priming conditions resulting from the introduction of single object trials.

condition	prime display		probe display		
	target	distractor	target	distractor	
NPSO	A	B	B	-	distractor(n) = target($n + 1$)
PPSO	A	B	A	-	target(n) = target($n + 1$)
COSO	A	B	C	-	One object this trial which was not presented the last trial.
SONP	-	B	B	C	distractor(n) = target($n + 1$)
SOPP	A	-	A	C	target(n) = target($n + 1$)
SOCO	A	-	C	D	None of the two stimuli matches the only preceding stimulus.
	-	B	C	D	

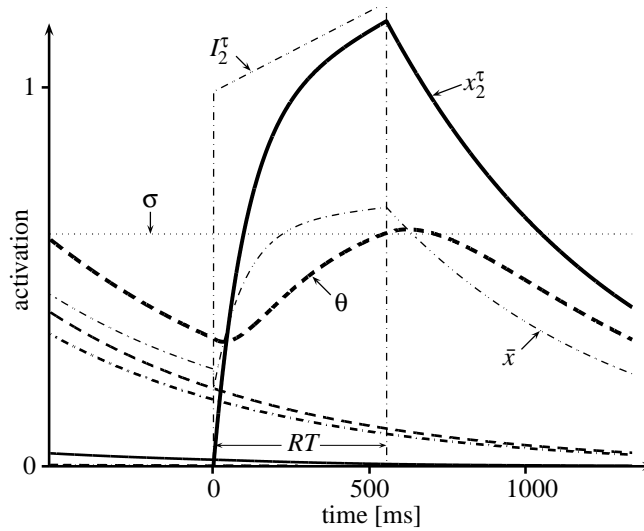


Figure 8. Activation-time diagram for the analysis of the behavior of the ISAM during SO-trials. There is only one object present. This results in a lower average activity \bar{x} . Without the sensitivity cutoff via σ , the reaction time in the case of an SO-trial would not be longer than the time necessary for perception and action initiation. In the trial directly after an SO-trial, the baseline activation is lower in comparison to non-SO trials, as the activation of the second object is lacking.

objects. The priming effects are clearly present without specific tuning of the model to this case, cf. Fig. 8. However, the global sensitivity level σ plays an important role, as it finally determines the moment of reaction.

Table 5. Reaction times for a response stimulus interval of 1500ms, together with variances and absolute effects in dependence of the condition of an exemplary simulated session. The usual priming conditions are not shown. The parameters are the same as in table 3.

condition	control	COSO	NPSO	PPSO	SOCO	SONP	SOPP
mean reaction time	525.84	407.48	427.72	299.58	573.55	624.80	548.20
effect	—	-118.36	-98.12	-226.26	47.70	98.96	22.36
variance of rt	14.78	22.91	24.77	36.51	19.98	34.30	27.70

Table 5 also displays the reaction times for trials that immediately succeed SO-trials. They are classified in dependence on the reoccurrence of the former object. It is obvious that a significant slowdown of reaction time after SO-trials is inherent to the model due to the lower overall activity if only one object representation is activated by the input. This justifies the separate consideration of trials immediately succeeding SO-trials. If these trials were subsumed under the classical conditions, they would artificially increase the variance. In experiments this slowdown can occur due to a disturbance of the response routine of subjects by SO-trials, where the switch back to two stimuli displays is also a distracting factor. We are currently running experiments to check whether this effect really is present in human behavior.

The observed effects during the presentation of single-object trials are readily explained in terms of the formal model: The overall activation that drives the threshold is lower in SO-trials, therefore θ takes longer to reach the activation level of the distractor during the next trial. This causes a longer delay until the correct object is singled out in order to allow for an unambiguous decision of the system.

5 Discussion

5.1 Modeling priming

The CISAM impressively reproduces experimental data without contradictions. Additionally it shows reasonable behavior when confronted with the touchstone of RSI-dependency. The implementation of the ISAM presented here is robust enough to provide predictions about stimulus constellations that have yet barely been considered in priming experiments so far. This circumstance serves as a good opportunity to test the ISAM experimentally. Among the many theoretical approaches to priming, we will select three of the most popular models and compare their implications to empirical results.

The distractor-inhibition model [Tipper, 1985, Houghton and Tipper, 1998] is one of the most influential theoretical accounts. Following this line of reasoning, the negative priming effect is supposed to be a cognitive index for the inhibitory component of selective attention. It is assumed that irrelevant stimuli representations are actively suppressed to support selection of the goal-relevant target stimulus, and that this inhibition persists for some time. When the former distractor becomes the behavioral relevant target in the subsequent display, responding is hampered because of the persistence of the inhibition imposed on it during the prime trial. However, shortcomings of this model emerge when explaining certain experimental results: Because negative priming is described as an after-effect of distractor inhibition, a facilitatory effect of ignored repetition trials without a distractor in the probe trial (e.g. [Tipper, 1985]) cannot be reasonably accounted for in terms of this model.

A second important account, the episodic retrieval model, has originally been proposed by Neill and colleagues (e.g. [Neill and Valdes, 1992]). They argue that negative priming is the result of conflicting information caused by a retrieval of the prime episode when exposed to the probe stimulus triggered by similarities of the two situations. The probe target thus causes retrieval of the prime episode due to repetition of the prime distractor. The information from the retrieved episode (i.e. “ignore the stimulus”) conflicts with the need to respond to this same stimulus in the current probe episode, resulting in a time-consuming process, which causes an increase of the reaction time, characteristic for negative priming. A particular advantage, in comparison to the other models, is its explanatory power regarding the influence of temporal discriminability of the prime episode relative to the preceding episodes. This is more easily accounted for by episodic retrieval than by inhibition-based models. The same is true for experimental evidence which shows that the effect increases quantitatively when the contextual similarity between prime and probe situation is increased (e.g. [Stolz, 2001]). However, the model falls short of explaining semantic negative priming effects, where the response to a probe target is only semantically related to the prime distractor (such as dog to cat), which are more easily accounted for by the inhibition model [Tipper, 1985]. Both of these models, the inhibition model and the episodic retrieval model, explain general reaction time increases in negative priming conditions in a straight-forward manner.

In contrast to the two previously described models, the temporal discrimination model (e.g. [Milliken et al., 1998]) does not assume selection processes during the prime task as the basis of negative priming. Instead, it assumes that negative priming is caused at the moment of response formation during the probe processing. Two response modes are postulated in the following context: the response can either be computed or directly retrieved from memory. Which of the two response modes guides behavior in the probe task depends on a categorization of the probe target as either “old” or “new”. If the probe target is categorized as new, a response is generated on the basis of perceptual analysis. Otherwise, if the same task situation has already been encountered, the response can rely on a direct retrieval of the former response. For a probe target in an ignored repetition trial, an ambiguity in the categorization process is assumed, resulting in a longer reaction time. But there is also empirical evidence which contradicts the predictions derived from this model: In a repeated distractor condition, the model predicts a slowdown in responding whereas a speed-up is repeatedly demonstrated in psychological experiments (e.g. [Frings, 2005]).

These considerations show that the modeling the negative priming effect is still in its developmental stages. Therefore we do not hesitate to implement the ISAM as a new contribution to the ongoing discussion of negative priming explanations. At first glance the CISAM looks similar to the inhibition based model [Tipper, 1985] as negative priming is the result of a negative interference. Considering details, the

two model differ in crucial aspects. In the CISAM, priming effects are an interplay of remaining activation from the prime display and activation driven by the probe input.

Generally, all effects are not present in the CISAM until the probe trial starts. For the inhibition based model, this is not the case, as the activation of the distractor is inhibited in the prime trial and negative priming is just an aftereffect. The negative interference is not due to a control mechanism ruling the prime decision as postulated in the inhibition based model, but an intrinsic interference within the neuronal circuits accounting for the prime distractor representation. The negative priming effect is thus obtained by the added "effort" of the distractor representation, which has to switch states from "do not respond to" to "respond to". This interference is more like the postulated conflict between memory traces and the current activation pattern responsible for negative priming in the episodic retrieval model. Another marking-off feature of the ISAM is that representations cannot be pushed below baseline, as the absence of a representation is modeled by zero activation. The interference only affects time constants of decay or rise towards input (5), (6). Similarities to Tipper's inhibition model can be found in the assumption of an external control mechanism responsible for the decision. But rather than inhibiting target activation in the probe trial, the control mechanism postulated in the ISAM boosts the target activation due to its semantic classification relative to the task.

Since the CISAM produces the priming effects at a very early stage of the probe trial, it displays no obvious similarities to the mechanisms presupposed in the temporal discrimination theory [Milliken et al., 1998]. In terms of the functional effectiveness, it can rather be placed between the two models first discussed, the inhibition and the episodic retrieval theory. The CISAM thus incorporates advantages from both approaches and integrates assumptions from both models into a more complete theory comprising all (positive and negative) priming effects.

5.2 Phenomenological and neural models

Modeling provides an attractive approach to attentional mechanisms and thus in particular to priming phenomena [Houghton and Tipper, 1994]. Firstly, mathematical modeling of a theory requires a precise formulation of the theoretical assumptions and mechanisms. This is of even greater importance as some of the explanatory models for negative priming presented above do not specify how and on what level attentional processes operate. Secondly, an explicit computational model can help to derive more specific predictions than possible from more abstract models, since not only qualitative but also quantitative predictions can be generated. Also, conducting computational experiments can produce new and even unexpected results that, in turn, can lead to experimental confirmation and extension of the model.

The CISAM presented here is implemented with effective equations. A refinement of neural networks seems desirable but cannot provide deeper insight in the mechanisms generating negative priming, as the effect appears at a high level of brain function where computation is strongly distributed. Therefore, no plausible neural model can be given at this stage of brain research. The reduction to an effective theory in contrast allows for direct observations of the functioning of the model itself without exhaustive investigations of the simulated data.

The difficulties of the model with short RSI point out the specificity of a certain approach that can never describe the whole behavior of the brain, which for example in the context of changing the RSI uses several different strategies, such as short term memory and long term memory when changing the RSI from 500 to 1500ms. With the present implementation, the ISAM moves up in line with the other explanations of priming effects like the inhibition or episodic retrieval approach. It shows possible simplifications of existing models, having in mind a minimal model that describes the generation of priming effects in the human brain.

5.3 The numerical implementation of the model

This section is devoted to a critical view on the properties of the current implementation. Mentioned are several points which are yet to be solved by extending the CISAM.

The numerical implementation revealed an insufficiency of the ISAM concerning RSIs that involve short-

term memory effects. For very short RSI its consequent implementation shows a reversal of priming effects. The reason for this strange behavior is an empty space of possible actions. At stimulus onset, the threshold level is still greater than any activation of the variables representing object recognition. Therefore a decision is made when the first variable reaches the threshold. An increase of this limited range of RSI requires the consideration of also low-level neurophysiological details, which will be incorporated in an improved version of the model.

Furthermore, our implementation is sensitive to the number of stimuli in one display. The factor $\frac{1}{2}$ in Eq. 8 is chosen for the situation of one target and one distractor. If multiple distractors were present, the model may not come to a decision. In general the factor has to be $\frac{1}{m}$ where m is the number of objects in one display. But a direct counting of the objects in the current display together with an adjustment of m is not acceptable as the dynamics should be able to autonomously adapt to this new situation. Finding a solution to this dilemma is one of the challenges a future version of the model has to overcome.

6 Conclusion

We demonstrate that priming effects, both positive and negative, can be explained in terms of the imago-semantic action model [Kabisch, 2003]. The main result of the present paper is the quantitative reproduction of experimental results by the computational formulation of the ISAM. This includes the speedup of responses to single-object presentations and the preservation of priming effects in these cases. We computationally substantiate the qualitative results expected from the original formulation of the ISAM. Present data does provide significant support for both positive and negative priming effects as well as the variants of NP2 and PP2. Nevertheless, more experimental data are needed in order to reach a more precise formalization of the model. They should include behavior in SO-trials, cases of multiple distractors as well as a variation of the saliency of the distractor.

In addition to a number of new experiments, which are currently under way, a next step should and will include the specification of the model by physiological constraints formulated mainly on the microscopic level. This way a more complex model could actually be less arbitrary if more knowledge is available on the interaction in neural networks at both small and global scales.

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