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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 27(27)

ISSN
1069-7977

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Publication Date
2005

Peer reviewed

Computational and Experimental Evaluation of the Attentional Blink: Testing The Simultaneous Type Serial Token Model

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Abstract

A reduced version of the Simultaneous Type Serial Token Model is presented. This model embraces two theories of temporal attention: Chun and Potter's two-stage theory and Kanwisher's types-tokens theory. We explain the proposed model and show how it reproduces key data from the Attentional Blink phenomenon. In addition, we verify experimentally predictions arising from the model.

Introduction

Rapid Serial Visual Presentation (RSVP) has been used extensively to explore how humans deploy attention over time (Chun & Potter, 1995; Kanwisher, 1987; Raymond, Shapiro, & Arnell, 1992; Weighelsgartner & Sperling 1987) Prominent amongst RSVP tasks is the Attentional Blink (AB), in which a decline in performance on a 2nd target (hereafter the T2) is observed when it is presented within between 100 and 500ms of the offset of a 1st target (hereafter the T1) (Chun & Potter, 1995; Raymond et al., 1992). Until recently, theoretical debates centred on informal explanations of the blink, which included the 2-stage model (Chun & Potter, 1995) and the Interference theory (Shapiro et al., 1997). These informal explanations have proved valuable in focusing formulation of experimental questions. However, the maturity of the field now makes it ripe for computational modelling. Accordingly, a number of models have recently been proposed (review: Bowman & Wyble, submitted).

The current paper focuses on the STST (Simultaneous Type Serial Token) model (Bowman & Wyble, submitted; Bowman, Wyble, & Barnard, 2004), for which we also use the shorthand ST^2. This paper reports the development of a reduced version of the approach (called the *reduced ST^2* model), which abstracts from some of the implementation details of the full model. Importantly though, the new model remains consistent with the theoretical principles that underlie the earlier ST^2 incarnation.

The focus of both ST^2 models is the *letters-in-digits* paradigm (Chun & Potter, 1995), in which the subject's task is to report the two letter targets placed in a stream of digit distractors. This experiment can be viewed as a canonical AB methodology since no task switch is involved between T1 and T2. The task originally used in (Raymond et al., 1992) involved a task switch, and is therefore more complex.

This paper serves to describe the reduced ST^2 model, its predictions, and, finally experimental verification of these predictions. Before introducing the new model, we briefly review necessary elements of the full ST^2 model.

The Full ST^2 model: Basic Principles

The full ST^2 model began as a rate-coded neural network elaboration of the theoretical two-stage model (Chun, 1997; Chun & Potter, 1995). The central idea behind their conception of RSVP processing is that the 1st stage can represent multiple items in parallel, but only for a short time (several hundred milliseconds). The 2nd stage is required for consolidation into a memory store that can persist until the end of the trial. However the 2nd stage is limited in its ability to process multiple items concurrently. Therefore, in order to limit interference in the 2nd stage, a gate is shut that denies entry to subsequent items. While waiting to be processed, these items are vulnerable to decay if they have been masked.

We agree with Chun (1997) that this model can be well implemented using the *types* and *tokens* framework described by Kanwisher (1987). In her theory, types represent possible kinds of items, devoid of context. In contrast, tokens represent memories that a given item was encountered, i.e. episodic (instance specific) information about the occurrence of an item. A token can be bound to any combination of types within its domain.

In the case of the letters-in-digits task, types would include all of the letters and digits, and one or more tokens would be assigned to represent the occurrence of the targets within an RSVP stream. The other key difference between types and tokens is that the latter are strictly sequential in nature, in that only one token may be in the process of binding at any one time. Hence, the name of our approach: *Simultaneous Type, Serial Token*. Types can be considered analogous to stage 1 of the two stage theoretical model, while our token implementation is the analogue of stage 2.

Stage 1. The full ST^2 model represented each potential item (i.e. each type) in an RSVP stream with a unique node that would be re-activated if the item occurred twice. We implemented a series of layers that represented steps of visual processing. At the 1st layer, distractors backward masked targets via inhibitory connections. Remaining activation from these masked traces reached the task-selective layer, at which the task demand system emphasized targets.

Stage 2. Target(s) in stage-1 could activate a token gate in stage-2, while strong lateral inhibition ensured only one token could be active at any time. The remainder of the token layer implemented dynamics, which insured, that after being active for a sufficient amount of time (approximately 200-300 msec), a token gate would be heavily suppressed to allow a 2nd token to be activated. While a token gate was active, it incrementally created binding links to any active items in stage 1. The binding links remained until the end of the trial, at which time they could be used to reconstruct the items in stage-1 that had been successfully encoded during that trial. In most cases, at lag 1 (i.e. when T2 immediately follows T1), one token would be bound to both T1 and T2. At lags 2-4 (i.e. when 1 to 3 distractors intervene between T1 and T2), one token would be bound to T1 with T2 insufficiently bound for retrieval. Beyond lag 4, after blink recovery, one token would be bound to T1 and another to T2.

The Blaster. Data from Chua, Goh, & Hon (2001), suggest that distractors immediately following the T1 are privileged in their ability to prime a subsequent T2. This suggests that attentional resources directed towards the T1 are not specific to it, but rather to a time window encompassing T1 and other information presented within 100ms of its offset, which includes the distractor immediately following T1.

Our model achieves this effect with a mechanism designed to provide a brief burst of excitation to all type representations, targets and distractors alike. Critically, this mechanism is suppressed while a target is being processed. This suppression protects a given target from interference by subsequent information. This implementation sacrifices T2 to protect T1.

In implementing an attentional resource within a neural network model, it immediately becomes clear why a mechanism of this sort might exist. Attentional resources directed specifically at the T1 would require some form of neural gating or phase-locking mechanism to restrict the resource to the T1 itself. An alternative implementation would involve many separate attentional mechanisms, one allocated to every possible target.

The blaster, on the other hand, can be implemented with a single node that spans the entire set of types. It is rarely the case that humans encounter items presented for as brief periods of time as are involved in the RSVP, therefore, the fact that this attentional resource can inadvertently spill over into subsequent distractors in this paradigm, would tend not to occur in real world situations. In fact, as suggested by experimental data we will later present, most of the benefit of this resource seems to arrive on the T1+1 slot, resulting in strong lag-1 sparing, and specific deficits in T1 when T2 is presented at lag-1.

The simplicity of this implementation allows us to consider neural biological candidates, chief among which is the Locus Coreleus (LC), a tiny structure that distributes noradrenaline to the entire cortex in short bursts. An alternative model of the LC's putative role in causing the attentional blink is described in Nieuwenhuis et al (in press).

An additional benefit of this mechanism is that it provides a single nodal point for closing the "attentional gate", required to limit access to the 2nd stage. While a token is in the process of being bound, a strong inhibitory projection disables the blaster, forbidding it from assisting a T2 that falls within the blink window (generally lags 2-4). Thus, a principle of the ST^2 model is that there is only one pulse of attentional enhancement per tokenization.

The Reduced ST^2 Model

We now move to discussion of the Reduced ST^2 model (Figure 1a), which is essentially the task selective layer, token gates, shutoff layer (which has not yet been discussed) and blaster of the full model. It is primarily the interaction of these parts that drive the temporal dynamics of the blink data that we will model. The extra layers in the full model provided functionality that is replaced in the reduced model by procedural code. Additionally, nodes representing the processing of distractors have been removed. These nodes were primarily involved in masking targets in the full model. Their functional role is now represented by a reduction in the strength of targets presented to the model.

In eliminating these nodes and reducing the time resolution of the simulation, we have vastly reduced the parameter space, and can run simulations at several hundredfold the speed of the more complex model. Unfortunately space does not permit us to elaborate the function of our model to the extent required to replicate it in detail. Instead we will focus our discussion on the theoretically salient points of its operation.

Operation. In testing this model, targets are presented to the T1 and T2 nodes at lags varying from 100 to 800 msec in 100 msec intervals, with time steps of 20 msec. Both T1 and T2 vary systematically in strength, reflecting natural variation in the featural distinctiveness of the different letters from the digit distractors, i.e. some letters appear to be more or less effectively masked by digits. Each lag in the modelled blink curve is a compilation of model accuracy across every possible combination of T1 and T2 strength at that lag. It is this variance in strength that explains why some T2's are able to survive the blink, and some T1's are missed entirely.

Later in the paper we will talk in terms of strong and weak targets, referring to putative differences in their inherent featural strength. For purposes of the model we designate weak targets as being the lower half of the variance applied to an item, and strong targets as being the upper half of this variance. Normally, targets vary between 2.5 and 5.1, so weak targets range from 2.5 to 3.8. Targets in the T1+1 and T2+1 blank condition (discussed below) vary from 7.5 to 10.1.

A critical distinction exists between the temporal relationship of types and tokens. Namely, types (for T1 and T2) are allowed to be coactive (barring the weak lateral inhibition that reduces, but does not generally eliminate coactivation), while tokens are restricted to being sequentially active. Token 2 is only permitted to be active if token 1 has reached its threshold and been shut down. This behaviour was implemented by the token trace layer in the full ST^2 model, but is dictated explicitly within the procedural code in this version.

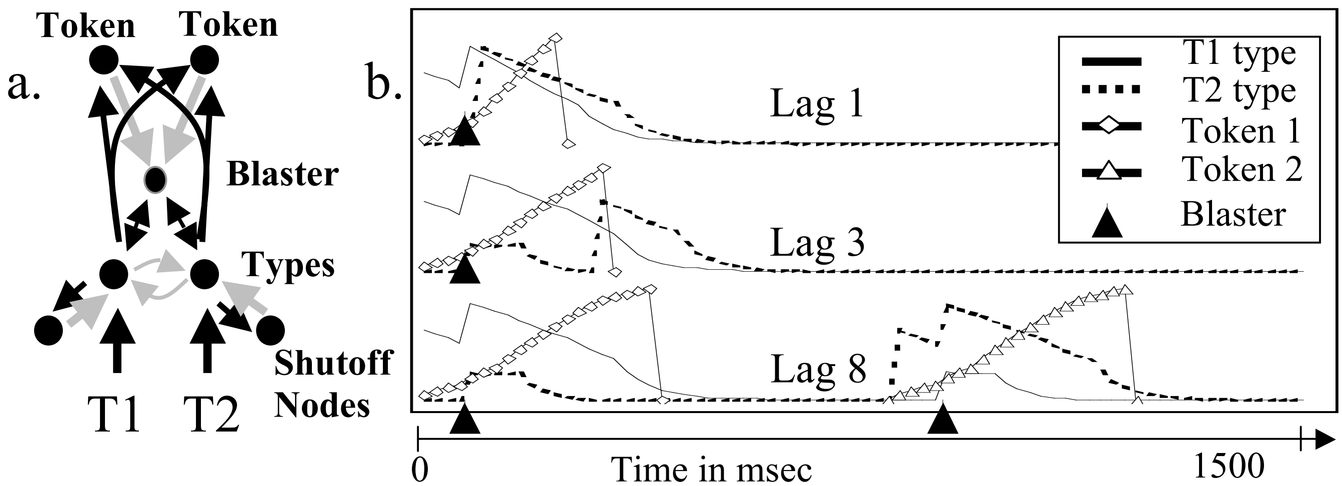

Figure 1: (a) Depiction of the reduced ST^2 model. Black lines represent excitation, while gray indicates inhibition. **(b)** Activation traces from the model illustrating three key behaviour patterns, demonstrated by lags 1, 3 and 8. Note that the blaster effects manifest 80 msec after it is triggered.

Shutoff nodes. We have not yet discussed the shutoff nodes, but they are essential in preventing a strong type from being tokenised multiple times. Gradually accruing activation in the shutoff nodes can cross a threshold, releasing a strong inhibitory projection onto their associated type nodes. Nodes of this sort can cause repetition blindness, see (Bowman & Wyble, submitted).

Blaster. The Blaster adds a small amount of activation to both T1 and T2 for 100 msec, which is enough to ensure an extended and amplified activation of a target that has recently been presented, but is insufficient to cause an item that has not been presented to be tokenized. This input of the Blaster to the type layer nodes is delayed by 80 msec. The Blaster has a refractory period of 250 milliseconds, and is suppressed by tokenization, see Figure 1a,b.

Binding. When at least one type node is coactive with a token, binding links are incrementally formed from that token to the type node. If two types are active, they will both receive binding links. The rate at which each link builds is proportional to the strength of the type node to which it projects. These links have no functional role in the encoding dynamics of the model and so are not present in Figure 1a. They are only considered at retrieval.

Performance evaluation. Performance is evaluated following 1500 msec of simulated time by testing the strength of binding links. Furthermore, binding links are only considered at retrieval if their associated token managed to be "completed" (i.e. crossed a threshold) during the presentation of targets. When two targets are retrieved, their temporal order is reconstructed probabilistically by considering the relative strength of binding links to T1 and T2 type nodes from tokens 1 and 2, even if those links are below threshold. Consequently, at lag-1, even though T2 is bound strongly to token 1 along with the T1, a slight degree of binding to token 2 will improve the chance of correctly recalling order. Weak, subthreshold bindings to Token 2 can occur even at lag-1 when T1 and T2 are particularly strong.

Functional dynamics

The functional characteristics of the reduced ST^2 model can be divided into three segments based on T2 lag: pre blink (lag 1), blink (lags2-4), and post blink (lags 5-8), see figure 1b.

Preblink. T2's presented immediately after T1 receive the full benefit of the Blaster, and thus, T1 and T2 are active simultaneously. There is some diminution of both as a result of the lateral inhibition, but they both remain active enough to be bound to a single token.

Blink. At lags 2-4, the blaster provides attentional enhancement in response to T1, which spills over to T2. However, this T2 activity has decayed by the time the T2 itself is presented. Furthermore, because the T2 arrives during or just after the tokenization of T1, the Blaster is unavailable to be fired a 2nd time. Thus, the T2 decays away without being tokenised and is thereby missed.

Post Blink. Presentation of the T2 at lags 5-8 is sufficiently late that tokenization of the T1 type is complete before T2 has decayed, and therefore the T2 is processed in like manner as are T1s, see Figure 1b.

Swaps. One of the strengths of this model is that it is capable of exhibiting ancillary effects of the AB, which are shown in Figure 2a,b. When T2s are presented at lag-1, both targets are bound to the same token. Thus, one of the main functions of the token system, i.e. recording the order of the presentation of items, is impaired. Hence, at lag-1, the model exhibits swaps: an inability to correctly recall the order of T1 and T2. This tendency in human subjects can be seen in (Chun & Potter, 1995).

T1 and T2 strength manipulations. If a blank is placed in the distractor stream at position T1+1, the blink is attenuated (Chun & Potter, 1995). Our model exhibits the same dynamic, see Figure 2a. A T1 that is unmasked by a missing distractor is presumed to cause a stronger activation strength, in accord with the full ST^2 model. This stronger trace drives the token system to a more rapid completion, allowing T2's to more easily outlive the blink. T2+1 blanks also allow T2's to outlive the blink, by evoking a very strong T2 trace that can be tokenised despite arriving during the blink. The Blaster is not necessary for tokenization of these stronger traces.

T1 Performance. The model correctly demonstrates a drop in T1 performance at lag-1, as a result of the interference of T2, see Figure 2b. The inhibition between T1 and T2 reduces the strength of the T1 node, and thus, its binding strength.

Predictions

Having explained the relevant dynamics of the model and fit several sets of data, it is incumbent on us to make predictions that we may be able to verify empirically. In discussing performance, T2|T1 will refer to T2 accuracy for those trials in which T1 was recalled. T2|NOT_T1 will refer to T2 accuracy for trials in which T1 was missed.

Prediction 1: The blink is temporal. Implicit within the design of our model is the assumption that the function of distractors is primarily to cause masking effects, weakening the target representations (Giesbrecht & Di Lollo, 1998). Accordingly, our model predicts that the blink is a function of the temporal relationship of targets in the stream, and not the number of intervening distractors. Consequently, if one doubles the rate of presentation of items, the AB effect will reflect the temporal relationship between the targets, not the sequential relationship. For RSVP streams presented at 50 msec per item, at lag-2 the T2 is following the T1 by 100 msec, and therefore, should exhibit complete sparing. Furthermore, at this faster rate the blink curve will recover by lag 12, instead of lag 6. We model this by using only weak T1 and T2 items, assuming that the 50 msec SOA will reduce bottom-up trace strength through enhanced masking. Model results are shown in Figure 2c.

Prediction 2: Increased T2 lag 1 performance with missed T1. The second prediction concerns the fate of T2s on trials in which the T1 was missed. In our model, this can occur because the T1 was too weak to be encoded, especially at lag 1 when T1 and T2 overlap most strongly. Despite being too weak to be encoded, the T1 still activates the Blaster, with resultant amplification of both the T1 and T2 traces. Recall that the arrival of the Blaster response is delayed, and amplifies the item in the following slot more fully than the item that triggered it. Therefore, a T2 at lag-1 for which the T1 was very weak, is going to receive a stronger amplification than it would have in isolation (i.e. analogous to the lag-8 case in which the T1 and T2 are temporally isolated). Consequently, when examining T2 trials for which T1 was missed, we find performance at lag-1 to be superior to baseline performance (as measured at lag-8, which is commonly equivalent for both T1 and T2). T2|NOT_T1 is equal to 92% at lag 1, compared to a normal lag-1 score of 81% for T2|T1. Baseline performance for T1 as well as T2|T1 at lag-8 is 85%.

Prediction 3: Labile Attention. In accord with Potter Staub & O'Conner (2002), our model predicts a changing relationship between T1 and T2 at different lags. When targets are separated by less than 200 msec, there is direct inhibition between the two simultaneously active type representations, hence strong T1's reduce T2 performance relative to weak T1's. At later lags, the attentional gate has closed, it is too late for T2 to be joined to Token 1. If T2 is encoded from lag3 onward, it will be bound to Token 2. Stronger T1's mean that Token 2 will be available more rapidly, thereby attenuating the blink. Figure 2e illustrates this pattern from the model. Weak T1s allow better T2 performance at early lags (1-2) due to reduced interference. Conversely, strong T1s evoke a much sharper and more rapid blink, that recovers more quickly.

Experimental Verification

Methods

To test these predictions we performed a letters-in-digits AB study. MATLAB v6.5 and the psychophysics toolbox (psychophysicstoolbox.org) were used to present trials to subjects on a Windows 2000 computer. Display timing rates were confirmed with photodiodes. 24 subjects were positioned in front of a 17" computer screen, displaying a white background, upon which black letters in 180 point Arial font were used as targets. Black digits in 220 point Arial were used as distractors. Two experiments were designed with different stimulus onset asynchronies. The 2nd was designed primarily to address prediction 1, but will also be cited to address 2 and 3.

After each trial, subjects were asked by a screen prompt to report the identity of the letters and the order in which they had seen them. Subjects were also advised to guess if they were not sure, but not to guess blindly. Despite this instruction, reversals of T1 and T2 by the subjects were not considered incorrect in the analyses. Temporal order of the response was only considered for the analysis of swaps.

Experiment 1: For 14 subjects, items were presented for 95 msec, followed immediately by the next item. RSVP streams were 18 items in length. T1 could appear in slots 5 to 8, while T2 could appear from lags 1-8 afterwards. At least 4 distractors followed T2.

With equal probability, items could have a blank in the T1 +1 slot, the T2 +1 slot, or no blank at all. Trial types were crossed in an 8x3 paradigm, with lag and blanks as primary factors. There were 144 trials per block, with three blocks per subject and 14 catch trials with no T2.

Experiment 2: For 10 subjects, items were presented for 45 msec, followed immediately by the next item. RSVP streams were 40 items long. T1 could appear in slots 9 to

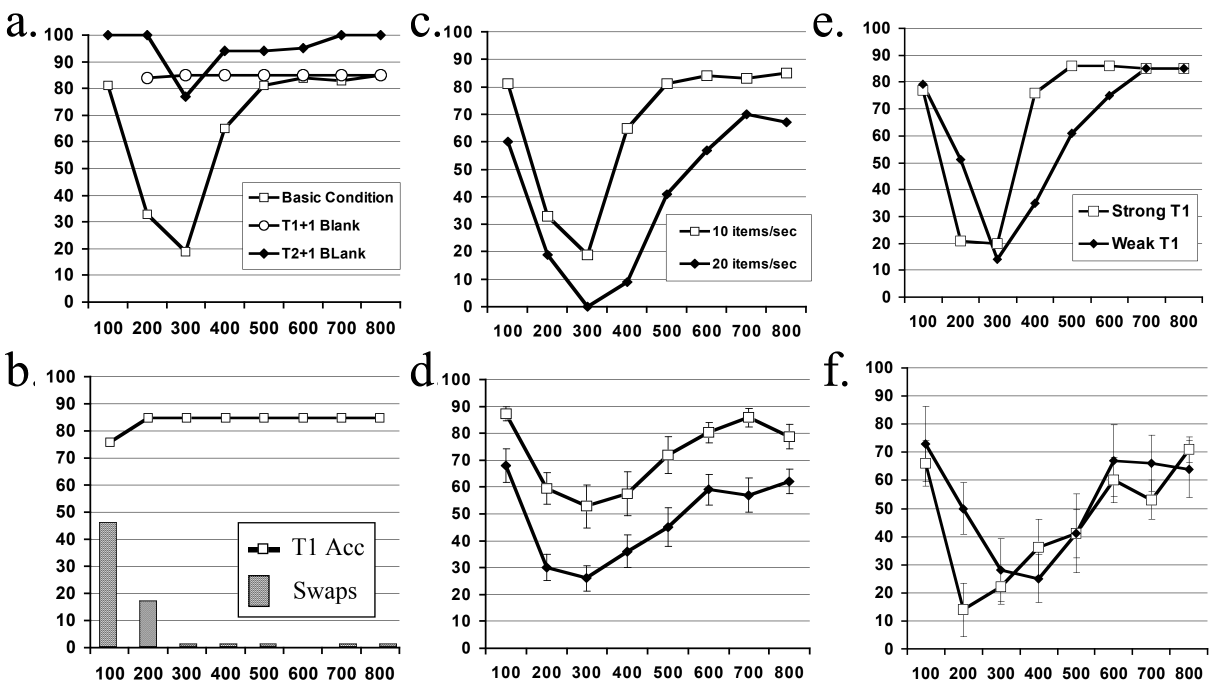

Figure 2: Simulation results and experimental data for 3 different conditions. In all figures, horizontal axis depicts lag in msec between T1 and T2. The vertical axis depicts accuracy of T2|T1 except for **(b),** which depicts T1 accuracy and swap data. **(a,b) Basic Results.** Performance of the model in the basic blink suite as described in the text. **(c,d) Prediction 1.** Simulation of the blink at fast and slow presentation rates (top), and data from experimental subjects (bottom). Note that the model was tuned to match data from Chun and Potter (1995), which had a deeper blink than obtained in our experiments. **(e,f) Prediction 3.** Depiction of simulated blinks for weak and strong T1's (top), and experimental data (bottom). Error bars represent standard error.

17, while T2 could appear at even lags 2-16 afterwards. At least 8 distractors followed T2. Subjects saw 96 two-target trials and 10 catch trials per block, for 3 blocks

Basic Results

We were able to record normal blink curves from our subjects as can be seen in Figure 2d. While we do not have space in this format for our replication figures, this experiment also confirmed the following effects from (Chun & Potter, 1995): T1 accuracy was reduced at lag 1, swaps were selectively found at lags 1 and 2, a T1+1 blank attenuated the blink. We also demonstrated that a T2+1 blank attenuated the blink, which is a novel result, but not surprising in the light of results which show that completely unmasking T2 attentuates the blink (Giesbrecht & Di Lollo, 1998). The remainder of this section will be devoted to novel results that we have predicted and now tested.

Strong and weak targets were separated by virtue of their performance in the catch trials. In experiment 1, strong targets were A H N T V Y, with an average recognition rate of 95%. Weak targets were B C D E P R with an average recognition rate of 84%. Medium targets were F G J K L U with an average recognition rate of 92%, these were not used in analysis of performance by target strength. In Experiment 2, sets strong and weak targets were largely similar. Strong targets were A K T Y V U and weak targets were B C D E F P with performance levels of 82% and 50% respectively. Performance was worse for all letters in experiment 2, presumably because of the stronger masking of the 50 msec SOA.

Prediction 1: The blink is temporal. The first prediction of the model is directly addressed by the contrast of the two experiments. What we have found is exactly what a temporal account of the AB would predict, namely, a blink curve that is dependent on the temporal separation of the targets, not the presence or absence of intervening distractors (assuming there are no blanks in the stream). Figure 2d demonstrates blink curves from experiments 1 and 2. Note, the nearly identical time course of the effect, bearing in mind that lag-2 in the 2nd experiment happens at the same time as lag-1 in experiment 1. The offset in performance level is presumably due to differences in T2 trace strength as a result of the stronger masking effects of the faster presentation rate. The only point of departure from the model is that the blink is of an exactly similar width in experiment 1 and 2. In the model, the weaker T1's used to simulate the faster presentation rate cause a longer blink as described by Prediction 3.

Prediction 2: Increased T2 lag 1 performance with missed T1. In experiment 1, T2|NOT_T1 performance at lag 1 was 94%, while T2|T1 performance was 87%. This confirms the prediction of the model, although unfortunately the results only approach significance (T test $p < .13$, two tailed). This is to be expected though, as the number of trials for the NOT_T1 conditions is fairly small and the values are approaching ceiling.

In experiment 2 the effect is more pronounced. At 100 msec (which is lag-2 in this experiment) performance for T2|NOT_T1 was 83%, well above both the baseline performance (60%) and sparing (68%) for the T2|T1 condition. The difference between the T2|NOT_T1 and T2|T1 conditions was significant (T-Test $p < .05$, 2 tailed).

Prediction 3: Labile attention. When trials were segregated by T1 strength in experiment 1, the two blink curves resemble those of prediction 2 qualitatively (not shown due to space restrictions), but are too close to be significantly different

For experiment 2, the difference between strong and weak items was inherently greater (82% and 50% baseline rates). Consequently, the strong/weak T1 manipulation caused blink curves that matched the prediction well. Weak T1's shifted the deepest point of the blink from 300 msec to 400 msec, allowing more sparing at 100 and 200 msec. Conversely strong T1's caused a blink with a deepest point at 200 msec, see Figure 2f. T2|T1 performance at 200 msec lag was significantly better in the weak T1 condition (T-Test $p < .007$ 2 tailed)

Discussion

We have presented a reduced ST^2 model that we believe captures the most salient aspects of the AB. This model can produce the following effects: changes in T1 performance, T1/T2 order inversions, and attenuation of the blink curve by blanks after T1 and T2. Our model also generated a series of predictions, which we were able to verify empirically.

We predict that the blink is temporal in nature. The influence of distractors is primarily in causing low-level masking of targets. Accordingly, it is the SOA between targets that is of primary importance in determining the characteristics of the blink. In our experiment, subjects exhibit lag-2 sparing at a rate of 20 items/sec that is nearly identical (relative to baseline levels of performance) to the time course of the 10 item/sec blink curve.

Our model describes a method of attentional enhancement that creates a temporal window surrounding a target, but is not specific to its identity. The verification of prediction 2 strongly supports this hypothesis, as it is difficult to imagine how T2 performance at 100 msec lag in the T2|NOT_T1 could be elevated well above the performance baseline for a T2 alone if it did not receive some kind of enhancement from T1.

Our model goes on to make a prediction concerning the changing nature of the relationship between T1 and T2 at different lags, and the predominantly temporal nature of the blink. Specifically, up to about 200ms post T1, the two targets directly compete with one another such that stronger T1s impair T2 more than weak T1's. At lags of 300-500ms, this relationship changes. T1 and T2 no longer directly compete. In fact a weak T1 causes a greater impairment of T2 at these lags, due to a longer binding duration. We feel that these results add a new temporal dimension to theoretical considerations of the AB. Our work suggests that there are two different means by which T1 and T2 interfere with one another. At early lags, there is direct interference between the targets, in line with the early hypothesis of (Raymond et al., 1992). At later lags, the system behaves as the two-stage model of (Chun & Potter, 1995).

Acknowledgements

This research is funded by EPSRC grant GR/S15075/01.

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