Selective Attention in Time: An Extended Model for Stimulus Onset Asynchrony (SOA) in Stroop Effect

Yingwei Yu and Yoonsuck Choe
Department of Computer Science
Texas A&M University
College Station, TX 77843-3112
Email: {yingwei,choe}@tamu.edu

***Abstract*— In stimulus onset asynchrony (SOA) experiments [11] with the Stroop task [25], the subject's response time of naming the colors is shorter when the subject knew that the color blocks were to be presented either earlier or later than the color-incompatible words, compared to the case when the blocks and words were presented simultaneously. This phenomenon suggests that the brain may estimate the onset time of the various stimuli and pay more attention to the time period in which the stimulus can be more relevant to the final response. In this paper, we interpret the SOA experiments with the Stroop task from a temporal attentional control perspective, and propose a computational model of *selective attention in time* to explain the SOA effect. The model extends the existing selection-through-accumulation model by Cohen and Huston [6] by adding temporal input-modulation mechanisms. Our results suggest that the concepts of attention over time ("selection of When") may need a fresh look, in addition to the selection of What, Where, and Which [13].**

***Index Terms*— Selective Attention in Time, Stimulus Onset Asynchrony, Stroop Effect**

I. Introduction

Selective attention refers to the competition between target resources (or relevant stimuli) and distracting resources (or irrelevant stimuli). As a result, the attended stimulus creates more reliable cortical activity than the unattended ones [26]. LaBerge and Samuels [16] [17] explained selective attention as an enhancement of target site (the corresponding principal cells of a thalamic nucleus). Some other theories pointed out that selective attention is object-based [1] [8] [10] [26] or space-based [22] [24] [26] [12]. These theories treated selective attention as a selection of What, Where, and Which [13]. Yet, selection in time has not been thoroughly investigated. In this paper, we will focus on attentional control in the temporal domain: the selection of "When".

A. Attentional Selection in the Temporal Domain

Attentional selection has been studied in visual search tasks (e.g. [5] [15]). In these tasks, target and distractor objects are presented simultaneously (Fig. 1a). Since the stimulus onset times are the same, there is no preference for particular time period: no modulation is needed to magnify or reduce the signal during a particular time frame. However, if the target and the distractor are presented at different time, modulation of the input signal may be needed if a certain time period is to be given preference. As shown in Fig. 1b, c, and d, when a relevant stimulus and an irrelevant stimulus are presented asynchronously, the desired modulation is to enhance the signal during the relevant time frame, and reduce the signal during the irrelevant time frame. Here, we are particularly interested in the attentional control mechanisms that show modulation of input signals over time. Such an attentional control in the temporal domain can be seen as *the selection of "When"*, which is different from space-based or object-based attention. The time-based modulation profile can be applied to all the stimuli, showing no preference over objects or locations. Time-based selection can provide an alternative explanation to the SOA effect in the Stroop task.

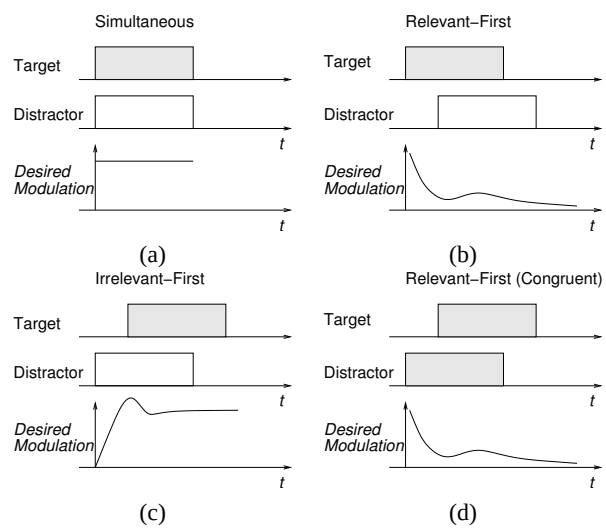


Fig. 1. **A schematic drawing of attentional control.** The target and distractor are defined by the task (e.g. in color-naming Stroop task, the target is a color block and the distractor a word). Distractor can be congruent with the target (as in (d): we mark the congruent stimuli pair in gray), or incongruent with the target (as in (a)-(c): the target and distractor stimuli pair are colored in gray and white). If the stimulus can provide sufficient information (that does not necessarily have to be a target: e.g., a congruent distractor) to invoke a response, the stimulus is defined as relevant, and otherwise irrelevant. (a) Simultaneous onset of target and distractor: input-modulation over time is not needed. (b) Relevant-first: The target (relevant) stimulus starts first, and the distractor (irrelevant) later. The desired modulation is to enhance the input in the early-stage and reduce the later-stage. (c) Irrelevant-first: The distractor (irrelevant) stimulus starts first, and the target (relevant) follows. The desired modulation is to reduce the input in the early-stage and enhance that in the later-stage. (d) Relevant-first (congruent): The distractor stimulus begins first, but unlike in case (c), the distractor can be a relevant stimulus. The desired modulation is to enhance the input in the early-stage as in (b).

B. SOA in the Stroop Task

Stroop task [25] tests how humans respond to a compound stimulus where the color information conveyed by the printed words is incompatible with the ink color (i.e., *incongruent case*: for a comprehensive review, see [18]). In the color naming task, stimulus feature from one dimension (color) is a target, while that from another dimension (word) becomes a distractor. The control-condition cards were the same as the experimental cards except that the text was replaced with colored blocks. The results showed that there was a significant (almost twice) difference in response time per item in the experimental case than in the control case [25].

Experiments on Stimulus Onset Asynchrony (SOA) investigated the time course of the Stoop effect [9] [11]. For example, Glaser and Glaser [11] presented words and colors with a set of target-first and distractor-first SOAs (Fig. 1b and c). In their configuration, the words were presented in white on a dark background, and the color in a colored block on the same background. The onset time of the word were 400, 300, 200, 100 or 0 ms before the time of color block presentation (distractor-first); or 0, 100, 200, 300, or 400 ms after the color block onset time (target-first).

The results by Glaser and Glaser [11] indicated that the Stroop phenomenon was not caused by the relative speed of processing of word or color. Interestingly, as shown in Fig. 2a, the response time is shorter for the distractor-first task (incongruent case). However, neither models based on selection-through-accumulation [7] [6] [2] (Fig. 2b) nor selection-through-attraction [21] can explain the phenomenon (see [23] for a summary). What could be the mechanism underlying such a time-course property in the SOA effect?

Roelofs [23] proposed the theory of selection-through-verification, which used a system named WEAVER++ to predict the SOA data. Although WEAVER++ yielded better results than all previous models, this model was not a purely connectionist model (i.e., semi-rule-based). More importantly, it omitted the possibility of attentional control over time.

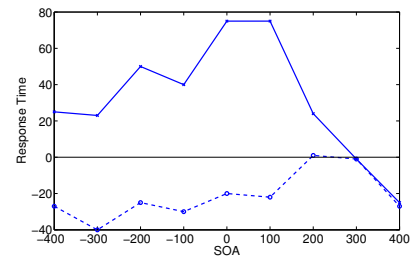
It is possible that attentional control over time can be learned: If the subject has experienced target (or the relevant cue) onset time that is always (or with a certain high probability) in a certain time offset from another stimulus onset, a neural process may adaptively adjust attention to enhance the relevant input or reduce the irrelevant input. From an attentional control perspective, we explore here, through attentional selection of "when", an alternative way to explain the SOA effect in the Stroop task.

The remainder of this paper is organized as follows. The next section (Section II) introduces our model. Section III describes the experiments and results, followed by discussions in section IV. We conclude with section V.

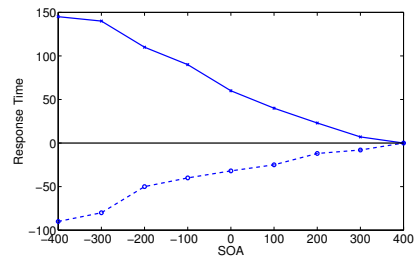
II. Model

A. Model Architecture

The proposed model contains three modules as shown in Fig. 3. Module I is the attentional control module, which involves two parts. The first part functions as a temporal learner and it generates inhibition profiles to modulate the input over time through the attentional gateway (Module III). The second part plays the role of a conflict monitor, monitoring the conflict in the responses that arose in the processing modules. Module I outputs to Module III control the signal magnitude.



(a) Experiment [11]



(b) Model [7] [6]

Fig. 2. **Human data and model result of SOA experiment.** In both (a) and (b), the results are for the color-naming task in the Stroop effect. The x-axis is the stimulus onset time. The negative time is for distractor-first case, and the positive time for the target-first case. The y-axis is the response time of human compared with the control case. Throughout this paper, the response time in the control case is used as a reference (solid line at $y = 0$). Therefore, positive response time means slower than the control, and negative means faster than the control. The solid lines are the response times of the incongruent case, while the dashed lines are those of the congruent case. (a) Human data by Glaser and Glaser [11]. Note that for the incongruent case, the peak of the curve is around time 0 and when the lag between distractor and target increases, the response time is reduced. (Redrawn from [11].) (b) Results from Cohen's model [7] [6]. Note that the incongruent cases are not correctly predicted compared to human data. (Adapted from [23].)

The second module employs the stimulus competition model, GRAIN, by Cohen and Huston [6]. There are two layers of neurons that are bidirectionally and recurrently connected as shown in Fig. 4. The processing network follows the GRAIN model's configuration as shown below:

$$\alpha_j(t) = \sum_i a_i(t) w_{ij} + e_j, \tag{1}$$

where t is time, α_j the post-synaptic potential of the j-th neuron, w_{ij} the synaptic weight as shown in the Fig. 4 (note that all the synapses are bi-directional, and $w_{ij} = w_{ji}$), and e_j the input from lower-level sensors. The pre-synaptic activity of neuron i is defined as:

$$a_i(t) = \sigma(\beta_i + \theta_i), \tag{2}$$

where σ is a sigmoid function (e.g. $tanh$ in our experiments), θ the threshold (number inside the circles in Fig. 4, and 0

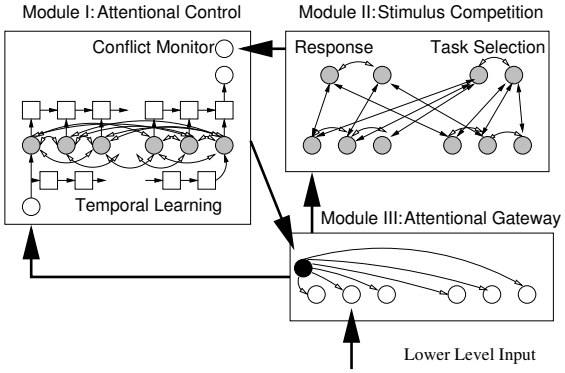


Fig. 3. **An overview of the model.** There are three modules: Module I - Attentional Control Module, Module II - The Stimulus Competition Module, and Module III - Attentional Gateway. The circles represent neurons (black circle: inhibitory neuron, gray circle: neuron with both excitatory and inhibitory synapses, white circle: excitatory neuron), and the squares delay units. Filled arrows represent excitatory, and unfilled arrows inhibitory synapses. The thick lines with arrows are interconnections between the modules, representing multiple parallel connections. See text for details.

otherwise), β_i a running average of post-synaptic potential over time with an averaging rate τ:

$$\beta_i = \tau\alpha_i + (1-\tau)\beta_i. \tag{3}$$

The constant τ was 0.01 in all the experiments. The two response neurons marked "RESPONSE" send their outputs to the conflict monitor [3]. When the difference in the two outputs accumulates to reach a threshold ($= 1$ in our experiments), an output of the perceived color is announced and that time point is recorded as the response time (GRAIN model, [6]).

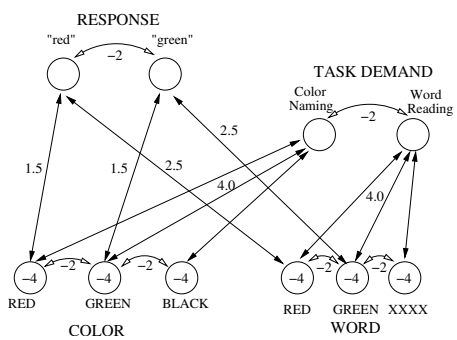


Fig. 4. **Module II: The Stimulus Competition Model.** Two layers of neurons that are bidirectionally and recurrently connected are shown. The circles represent neurons. Filled arrows represent excitatory synapses, and unfilled arrows inhibitory synapses. Numbers in the circles represent the threshold of that neuron. (Redrawn from [6].)

The third module is an attentional gateway. It forwards the input from lower level visual pathway to module I and II. It reads the attentional control feedback from module I and regulates the input magnitude through an inhibitory neuron. The details of temporal control will be introduced in section 2B.

This model architecture follows the "triangle circuit" theory proposed by LaBerge [13] [14]. The triangle circuit includes three aspects of attention: expression, enhancement mechanism, and control. The "expression aspect", as indicated by LaBerge, corresponds to the clusters of neurons in the posterior and anterior cortex that serve cognitive functions. They map to the processing module (Module II) in our model. The "enhancement mechanism" maps to the thalamic nuclei as the attentional gateway in our model (Module III). The "control" maps to the attentional control module (Module I).

B. Temporal Control Profile

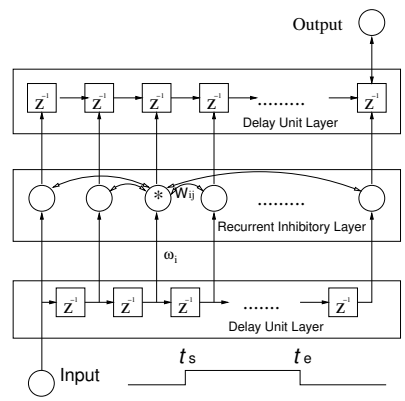


Fig. 5. **Module I, part 1: A solution for temporal learning.** There are three layers in this module: the first layer is a delay unit layer, which transfers the temporal sequence into spatial representations into the second layer. The second layer contains mutually inhibitory neurons. In the figure, only the connectivity for the neuron marked with a star is shown. The other neurons in this layer are similarly connected. The third layer is another delay unit layer, which replays the output from layer two into a temporal sequence. See text for more details.

The temporal input-modulation profile can be learned by a neural network as shown in Fig. 5. The circuit updates the connection weights for every instance of SOA stimulus. Therefore, the circuit becomes more accurate over time in predicting the onset time of a target stimulus. For example, let the stimulus (relevant or irrelevant) occur at time t_s and vanish at time t_e. (Note that the "relevant stimulus" does not necessarily mean the "target", because in the congruent case, the "distractor" can also be relevant to the final response, and the brain may use this relevant information as a cue to predict.) The input neuron in Fig. 5 forwards the signal 1 for relevant stimulus or -1 for irrelevant stimulus during time period t_0 and t_e, and 0 at other times to the delay unit layer. The delay units in this layer then converts the temporal sequence into spatially distributed signals $\{s_0, s_1, ..., s_{n-1}\}$ and update the weights (ω_i, where i is the index of neuron) of the synapses between the feedforward delay unit layer and the recurrent inhibitory layer. For relevant stimulus, there will be an increase in the synaptic weight by a factor of γ (similarly for irrelevant stimulus, a decrease) in the synaptic weight. If there is no input, the weight remains the same. Therefore, the synaptic weights can be updated based on the input to the neuron in the recurrent inhibitory layer $i(t)$ as follows:

$$\omega_i(t+1) = \omega_i(t) + \gamma i(t) w_i(t). \tag{4}$$

The synaptic weight W_{ij} from unit j to i in the middle layer employs a difference of Gaussians (DoG) neuronal interaction profile, which can be defined as follows:

$$W_{ij} = G_{\sigma_c}(\mid i - j \mid) - G_{\sigma_s}(\mid i - j \mid), \tag{5}$$

where σ_c and σ_s are standard deviation for the center and surround Gaussians, and the function G is a Gaussian function with mean at zero and standard deviation of σ:

$$G_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \tag{6}$$

The Gaussian kernel in the inhibitory layer can smooth and increase the contrast. If we treat the input sequence $\{s_0, s_1, ..., s_{n-1}\}$ as a vector $\mathbf{s}$, the output $\mathbf{r}$ of the middle layer can be obtained by the equation below (Yu, Yamauchi, and Choe [27]):

$$\mathbf{r} = (\mathbf{I} - \mathbf{W})^{-1}\mathbf{s} \tag{7}$$

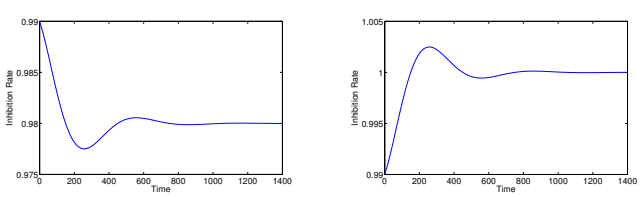
where $\mathbf{I}$ is an identity matrix, and $\mathbf{W}$ the weight matrix defined in 5.

The third layer converts the spatial sequence $\mathbf{r}$ back into temporal control sequence $\eta(t)$ at the output neuron through a series of delay units. The output neuron excites the inhibitory neuron in Module III. This way, the input signal gets modulated according to the temporal input-modulation profile.

In our experiments, for practical reasons, the shape of the temporal control sequence $\eta(t)$ at the output neuron (for both relevant-first and irrelevant-first cases) were approximated by the following exact equation:

$$\eta(t) = \eta_0 + ke^{-t/\tau}\cos(\omega t), \tag{8}$$

where η_0, k, τ, and ω are free parameters to control the shape of the profile. The parameter η_0 defines the baseline of the inhibitory profile, k the relevancy ($+1$: distractor-first; -1: target-first), and τ and ω the decay temporal factors. The inhibitory modulation rate $\eta(t)$ is plotted in Fig. 6.



(a) Relevant-first task (b) Irrelevant-first task

Fig. 6. **Temporal control profiles.** (a) Relevant-first case ($k = 0.01$, $\tau = 200$, $\omega = \pi/300$, $\eta_0 = 1 - 2k$). (b) Irrelevant-first case ($k = -0.03$, $\tau = 200$, $\omega = \pi/300$, $\eta_0 = 1$).

In the brain, the learning site of the temporal attention control can be in the hippocampus, the basal ganglia, and the prefrontal cortex [20]. In the next section, we will show that the response time can be significantly changed by different temporal input-modulation profiles.

III. Experiments and Results

A. Experiment 1: Using Irrelevant Control Profile for Distractor

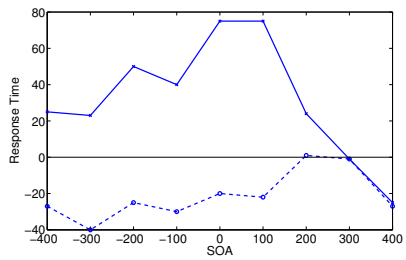
In the first experiment in [11], Glaser and Glaser used a set of 48 SOA cases (with $1/3$ congruent cases) which were randomly ordered. Due to the low rate of congruent cases, the distractor was more likely to be irrelevant to the response. For the simulation of this experiment, we employed the temporal input-modulation profile shown in Fig. 6a (relevant-first) for the target-first task, and that in figure 6b (irrelevant-first) for the distractor-first task. The model predictions and human data in color naming task are compared in Fig. 7. Similar to the human data, the response time of the incongruent case predicted by the model has a peak at around 0 ms SOA, and decreases in both positive and negative directions. In contrast, the model results by Cohen, Dunbar, and McClelland [7] [6] (Fig. 2b) only decreased monotonically toward positive SOA, and it achieves maximum response time at the negative end of SOA (at -400ms). In the congruent case, our model correctly predicted that the response time is below the control baseline ($y = 0$). The approximate response time of the model (solid curve below the control baseline) matches well with the human data (the dashed curve below the control baseline).

These results indicate that, through temporal attentional control, the response time is reduced when the stimuli have a longer lag between their onset time. Therefore, when two stimuli occur more separately over time (for both positive SOA and negative SOA), neural processes can discriminate the two by reducing the input magnitude during the presentation of the distractors.

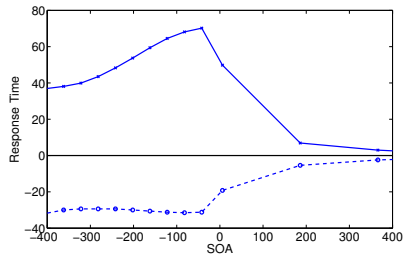
B. Experiment 2: Using Relevant Control Profile for Distractor

In the previous experiment, we used irrelevant-first input-modulation profile for distractor-first SOA cases, and thus the distractor is treated as irrelevant to the response. Now we are interested in knowing how the choice of irrelevant-first or relevant-first profiles can affect the response time. In this experiment, we will apply relevent-first modulation profile for the distractor-first SOA cases.

As shown by the results of the model, the response time of the incongruent case (the solid curve above line $y = 0$ in Fig. 8b) takes longer than the result in experiment 1 (the dashed curve above line $y = 0$). The response time of the congruent case (the solid curve below line $y = 0$ in Fig. 8b) is shorter than the result in experiment 1 (the dashed curve below line $y = 0$). One comparable human experiment of "relevant distractor" in SOA was done by Glaser and Glaser [11]. They did an experiment with a 80% probability of congruent cases. Since there was high probability of congruent cases, in the distractor-first case, the distractor may not be a real "distractor" but more likely a cue for the "target". In Fig. 8, the changes in response time in those two experiments are marked by the arrows in both the human and the model data in Fig. 8a and b. The human data showed that the subjects appeared to

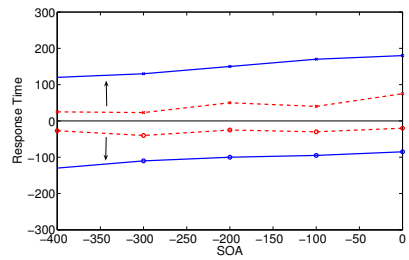


(a) Experiment [11]

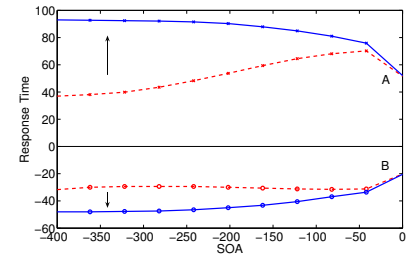


(b) Model

Fig. 7. **Human data and model result of SOA experiment.** In both (a) and (b), the results are for the color-naming task in the Stroop effect. The solid lines are incongruent case, and the dashed lines congruent case. (a) Human data by Glaser and Glaser [11]. Note that for the incongruent case, the peak of the curve is around time 0 and when the lag between distractor and target increases, the response time is reduced. (Adapted from [23].) (b) Model prediction. This result indicates that through temporal attentional control, the response time is reduced when the stimuli have a longer lag between their onset time points. The model response time is scaled by 0.3.



(a) Experiment [11]



(b) Model

Fig. 8. **Result of Experiment 2.** (a) Human Data. (Redrawn from [11]) (b) Model Data. Similar to human data, the incongruent case's response time is increased than in the first experiment, while for the congruent case it is reduced. The model response time is scaled by 0.3. In both (a) and (b), the solid lines are results of experiment 2 with high probability of congruent cases. The dashed lines are from experiment 1 with low probability of congruent cases. The curves above line $y = 0$ are for incongruent cases, while those below line $y = 0$ congruent cases.

have reduced response time for all the incongruent cases when compared to the results in the first experiment.

However, compared to the human data, a discrepancy arises at SOA time 0 in the model results (as marked "A" and "B" in the figure): the solid curve (data from experiment 2, high probability of congruent case) converges with the dashed curve (data from experiment 1, low probability of congruent case). This is because our model is not designed to handle probability of congruent case at current stage. What the model demonstrated is how the relevancy profile of the distractor can affect the response time. Approximately, the higher probability of congruent cases in distractor-first task, the temporal input-modulation profile has a peak at an earlier position over time. Moreover, when the time lag decreases to zero, the temporal input-modulation profile does not make any difference to both of the stimuli, and therefore in such a case the whole system degrades to module II (Fig. 4) which has no ability to handle the change of the probability of the congruent cases. To address the learning mechanism of non-temporal factors, which is purely contributed by the distributions of the training cases, more research may be needed. For our current model, it can demonstrate that the shift of attention input-modulation profile in time domain can affect the level of conflict between different stimuli, and when the brain pay more attention to the time period of the relevant stimulus onset, the overall response time is reduced. As a side effect, the response time in the incongruent case becomes longer due to the incorrect selection of time during which the stimulus is irrelevant.

IV. Discussion

Time-based selective attention is different from space-based or object-based attention control mechanisms. Time-based attentional control adjusts the input magnitude according to the temporal relevancy of the stimulus, e.g. the occurrence of the congruent stimulus, to the overall response to color in the Stroop task. The temporal input-modulation profile can be given a priori from a higher level cognitive module, or obtained through reinforcement learning. The high peak in the temporal input-modulation profile means the "expected" moments and the input should be enhanced in such a case; the low valley can be interpreted as "noisy" moments and the input should be inhibited. Through sampling the stimulus and monitoring the internal response, the "expected" and the "noisy" time frames can be adaptively learned. Therefore the brain can use less computational resources for faster and more accurate responses for repeated tasks.

The time-based selection is neither an early-selection (e.g., filter theory by Broadbent [4]) nor a late-selection (e.g., [19]). The brain not only controls the inputs at an early-stage as in module III, but also evaluates and learns at a late-stage as in module I. The evaluation of response relevancy must consider the relationship between high-level motor responses and the low-level sensory input. In this respect, our understanding of selective attention is similar to the "enhancement of a target site" theory by LaBerge and Samuels [16], where ours is

"enhancement of stimulus in a relevant time frame".

One limitation of our current model is that it does not evaluate whether a stimulus is relevant or irrelevant. At current stage, the relevancy of the input to the response was given (1 for relevant, -1 for irrelevant input). However, this functional block of relevancy evaluation can be extended by checking if a stimulus is sufficient to invoke a correct response, and if so, it can be labeled as a relevant stimulus. For example, in congruent case of color-naming task, a first appearing word "red" that is followed by a red block is sufficient to invoke a verbal response "red", therefore, it is a relevant stimulus and the association can be learned.

The idea of selective attention over time can be verified through functional magnetic resonance imaging (fMRI) experiments (similar to the experiments for space-based attention [5] or object-based attention [26]). For example, we can design experiments to show subjects a sequence of words on a computer screen, and at some random time point play a bell sound. The subjects are to remember the words only at the point when the bell is heard. If the onset time of sound has a narrow distribution over time, it is expected that the brain activities of the thalamus and certain brain areas (e.g. prefrontal cortex or basal ganglia) will increase in a short period preceding the sound onset time. If so, it demonstrates that through learning, the brain has come to "expect" or "prefer" a certain time frame, i.e. selective attention of "when".

V. Conclusion

Time-based attentional control mechanism provides an alternative explanation to the SOA effects in the Stroop task. The attention mechanism in the brain involves the thalamocortical circuit and other brains areas (e.g. prefrontal cortex, hippocampus, or basal ganglia) that carry out learning and higher level cognitive functions (e.g. defining the task and comparing the relevancy of input stimulus). The control can be realized by an internally learned temporal input-modulation profile, and inhibitions to the low-level sensory inputs. Although the idea of selective attention over time and the model suggested in this paper await both more theoretical and empirical confirmations, for the first time it expanded the concept of selective attention into the temporal domain: the selection of "When". Time-based attentional control can enhance the overall system performance.

Acknowledgment

The authors would like to thank Takashi Yamauchi for helpful discussions.

References

[1] G. Baylis and J. Driver. Visual parsing and response competition: the effect of grouping factors. *Percept Psychophys*, 51:145–162, 1992.

[2] M. Botvinick, T. S. Braver, D. M. Barch, C. S. Carter, and J. D. Cohen. Conflict monitoring and cognitive control. *Psychological Review*, pages 623–652, 2001.

[3] M. Botvinick, L. E. Nystrom, K. Fissell, C. S. Carter, and J. D. Cohen. Conflict monitoring versus selection-for-action in anterior cingulate cortex. *Nature*, pages 179–181, 1999.

[4] D. E. Broadbent. *Perception and communication*. Pergamon Press, London, 1958.

[5] L. Chelazzi, E. Miller, J. Duncan, and R. Desimone. A neural basis for visual search in inferior temporal cortex. *Nature*, 363:345–347, 1993.

[6] J. Cohen and T. Huston. Progress in the use of interactive models for understanding attention and performance. In C. Umilta and M. Moscovitch, editors, *Attention and Performance XV: Conscious and Nonconscious Information Processing*, pages 453–456. MIT Press, Cambridge, MA, 1998.

[7] J. D. Cohen, K. Dunbar, and J. L. McClelland. A parallel distributed processing account of the stroop effect. *Psychological Review*, 97:332–361, 1990.

[8] J. Duncan. Selective attention and the organization of visual information. *Journal of Experimental Psychology: General*, 113:501–517, 1984.

[9] F. Dyer. The duration of word meaning responses: Stroop interference for different preexposures of the word. *Psychonomic Science*, 25:229–231, 1971.

[10] R. Egly, J. Driver, and R. Rafal. Shifting visual attention between objects and locations: evidence from normal and parietal lesion subjects. *Journal of experimental psychology General*, 123:161–177, 1994.

[11] M. O. Glaser and W. R. Glaser. Time course analysis of the stroop phenomenon. *Journal of Experimental Psychology: Human Perception and Performance*, 8:875–894, 1982.

[12] R. M. Klein and D. I. Shore. Relationships among modes of visual orienting. In S. Monsell and J. Driver, editors, *Attention and Performance XVIII: Control of cognitive processes*, pages 195–208. MIT Press, Cambridge, MA, 2000.

[13] D. LaBerge. *Attentional processing: The brain's art of mindfulness*. Harvard University Press, Cambridge, MA, 1995.

[14] D. LaBerge. Attention, awareness, and the triangular circuit. *Consciousness and Cognition*, 6:149–181, 1997.

[15] D. LaBerge, M. Carter, and V. Brown. A network simulation of thalamic circuit operations in selective attention. *Neural Computation*, 4:318–331, 1992.

[16] D. LaBerge and S. J. Samuels. Toward a theory of automatic information processing in reading. *Cognitive Psychology*, 6:293–322, 1974.

[17] D. LaBerge and S. J. Samuels. Toward a theory of automatic information processing in reading. In H. Singer and R. B. Ruddell, editors, *Theoretical models and the processes of reading*. International Reading Association, Newark, DE, 1985.

[18] C. M. MacLeod. Half a century of research on the stroop effect: An integrative review. *Psychological Bulletin*, 109:163–203, 1991.

[19] D. A. Norman. Towards a theory of memory and attention. *Psychological Review*, 75:522–536, 1968.

[20] R. C. O'Reilly and M. J. Frank. Making working memory work: A computational model of learning in the prefrontal cortex and basal ganglia. *Neural Computation*, 18:283–328, 2006.

[21] R. H. Phaf, A. V. D. Heijden, and P. T. W. Hudson. Slam: A connectionist model for attnetion in visual selection tasks. *Cognitive Psychology*, 22:273–341, 1990.

[22] M. I. Posner. Orienting of attention. *Quarterly Journal of Experimental Psychology*, 32:3–25, 1980.

[23] A. Roelofs. Goal-referenced selection of verbal action: Modeling attentional control in the stroop task. *Psychological Review*, 110:88–125, 2003.

[24] S. Shomstein and S. Yantis. The role of strategic scanning in object-based attention (abstract). *Journal of Vision*, 2:437a, http://journalofvision.org/2/7/437/, doi:10.1167/2.7.437., 2002.

[25] J. Stroop. Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, 18:643–662, 1935.

[26] S. Yantis and J. T. Serencesy. Cortical mechanisms of space-based and object-based attentional control. *Current Opinion in Neurobiology*, 13:187–193, 2003.

[27] Y. Yu, T. Yamauchi, and Y. Choe. Explaining low level brightness-contrast visual illusion using disinhibition. *In A. J. Ijspeert, M. Murata, and N. Wakamiya, editors, Biologically Inspired Approaches to Advanced Information Technology, Lecture Notes in Computer Science 3141*, pages 166–175, 2004.