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Authors

Domijan, Drazen
Setic, Mia

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Adaptive Resonance as a Neural Basis for Conceptual Semantics

Dražen Domijan (ddomijan@ffri.hr)

Department of Psychology, Slavka Krautzeka bb
51000 Rijeka, Croatia

Mia Šetić (mia-setic@ffri.hr)

Department of Psychology, Slavka Krautzeka bb
51000 Rijeka, Croatia

Abstract

Experimental data on the interaction between perception and conceptual processing in the domain of motion was modeled by using an adaptive resonance circuit. It was shown that the same mechanisms that are responsible for stable category learning also support perceptual simulation of conceptual knowledge. The model is implemented as a dynamical system, which is able to switch between perception mode, where the network dynamics is driven primarily by the sensory input, and the simulation mode, where the network dynamics is driven by the conceptual input from the internal sources. Computer simulations showed that the differences in reaction times in behavioral studies arise from the match (or mismatch) between the sensory input and top-down learned expectations when the network switches between perception and the simulation mode.

Keywords: Adaptive Resonance Theory; Conceptual Processing; Perceptual Simulation; Stability-Plasticity Dilemma; Symbol Grounding.

Introduction

Recent theoretical advances in knowledge representation suggest that concepts are not independent from perceptual, motor or emotional contexts, in which their exemplars are observed. Rather, perceptual representations are reactivated during abstract conceptual processing and constitute an important component of comprehension. Barsalou (1999) proposed a theory of perceptual symbol systems which posits a perceptual simulation as a mechanism for the interaction of perception and conceptual knowledge. According to Barsalou's (1999) idea about a particular concept activating the same sensory and memory pathways that are used during perception of the referent object. In this way, many properties of the referent object that are not explicitly mentioned become readily available for inspection and further processing.

The empirical prediction of the theory is that traces of perceptual simulation should be evident in behavioral signatures such as the reaction time data, when the perceptual stimulus matches or mismatches with the content of the simulation. For instance, Zwaan, Stanfield and Yaxley (2002) showed that the implied shape of the object mentioned in the sentence speeds-up recognition if the image presented has implied shape. It is interesting to note that in some situations researchers revealed that perceptual simulation produces an increase in the speed of processing (Zwaan, Madden, Yaxley, & Aveyard, 2004), while in other

situations it may produce decrease, that is, slower reaction times (Estes, Verges & Barsalou, 2008; Kaschak *et al.*, 2005). Recent brain imaging studies revealed a close connection between brain areas for perception and for conceptual knowledge about perceptual attributes such as color, motion etc. (Martin, 2007).

One critique of the theory of perceptual symbol systems and related ideas is that they lack a formal specification. While the theory predictions have been successfully probed in the empirical studies it still awaits rigorous mathematical treatment (Barsalou, 2008). At the neural level, Pulvermüller (1999, 2001) proposed a concept of word webs which integrate activation in different brain regions related to the same concept. He suggested that Hebbian learning is responsible for creating word webs, but this is not precise enough to explain results from behavioral studies mentioned above.

How could empirical findings about the relation between perception and conception be simulated by using a neural network? We suggest that the Adaptive Resonance Theory (ART) provides an adequate framework for understanding the neural basis of conceptual semantics (Carpenter & Grossberg, 1993). ART was designed to solve the problem of stability of learning in a non-stationary environment. Many neural network algorithms are able to detect and represent statistical regularities in the input. However, when input statistics is altered (as it often happens in real-life situations), old codes are erased, despite the fact that they may still be predictive and useful. For instance, we do not forget our name or date of birth just because we move to another city. This is known as a catastrophic interference.

According to Grossberg (1980), the solution to the problem of catastrophic interference is to compare the sensory (bottom-up) data with the learned (top-down) expectations. If the input pattern is matched with one of the previously learned codes (categories) it is recognized as a familiar pattern and resonance occurs between the sensory pattern and the top-down activation. On the other hand, if there is a large mismatch between the input pattern and the learned code, a reset signal is issued which resets the whole system and initiates a search for another learned code that may match with the input. If there is no learned code that is sufficiently similar to the input pattern, a new neural tissue is committed to learn the presented pattern and to establish a new category. Therefore, the previously learned codes are protected by the mismatch detection and they will not be

erased in the presence of the novel patterns. Here, we suggest that the same top-down pathways that are needed to stabilize learning are also used during conceptual processing in order to reactivate perceptual patterns associated with concepts. In other words, the existence of perceptual simulation is a natural consequence of the brain mechanisms which prevent erosion of previously memorized patterns.

Model Description

ART is a three-layer architecture with two auxiliary mechanisms for controlling network activity (gain control mechanism and reset mechanism) as shown in Figure 1. Layers are denoted as F0, F1 and F2 (Carpenter & Grossberg, 2003). F0 is an input layer which registers the pattern of sensory stimulation. F1 layer reads-out the sensory pattern from F0 and combines it with the top-down expectations arriving from the F2 layer. The activation flows from F1 to F2 and passes through a filter of adaptive weights. The F2 layer is a winner-takes-all network which represents the category or the concept that best match the sensory input. The gain control mechanism, G, enables distinctions to be made between sensory stimulation and internal activation. Only sensory stimulation is allowed to reach the supra-threshold activation and to ignite resonance between F1 and F2 layers. Finally, the orienting subsystem, R, watches for the difference between the bottom-up activation from F0 and the top-down activations from F2. It produces a reset signal when the difference is larger than a certain prescribed value. The reset signal shuts-off the currently active F2 node and initiates a search for another F2 node that will provide a better match to the sensory pattern.

Modified ART circuit

In order to explain the results from behavioral studies we introduced several modifications with respect to the original architecture. Firstly, we introduced the output nodes, M, which read-out activity from the F2 layer. These nodes are designed to mimic accumulation of evidence for particular alternatives and motor preparation. They are modeled as leaky accumulator units which integrate incoming signals until they reach the threshold (Usher & McClelland, 2001). The network is considered to make a motor response when one of the nodes in the output layer exceeds the threshold level of activation. Secondly, we modified properties of the gain control system in order to distinguish perception from perceptual simulation. We propose that the perceptual simulation induces the cycle of mutual activation of F1 and F2 layers, similar to that observed during perception. However, an important distinction is that during perceptual simulation this activation is reduced due to the inhibition from the gain control unit. Therefore, there is no full-fledged resonance between F1 and F2 as during perception. Traces of perceptual simulation could influence perception when the network is switched from simulation mode to the perception mode. This occurs when the activity of the gain control unit changes from the low level to the maximal

level. Also, perception could influence simulation when the network is switched from the perception mode to the simulation mode. Differences in reaction time data are explained as a consequence of activation of the gain control and reset mechanisms which speed-up or slow-down dynamics of the network.

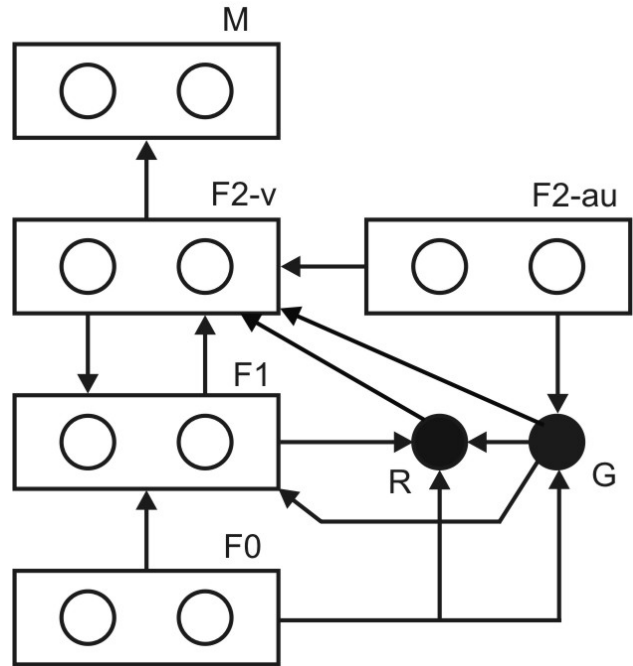


Figure 1. Modified ART circuit for perceptual simulation.

Perceptual simulation is implemented in the model as a weak influence of the one ART module on another ART module responsible for different modality or different perceptual attribute within the same modality. For instance, in the Figure 1 we depicted how is visual ART module, F2-v, influenced by the auditory ART module, F2-au, as when we heard a sentence and tried to understand it.

In order to simulate properties of the experimental tasks mentioned in the Introduction, we need to consider the interaction between two ART modules. For instance, we could consider a special ART module for visual modality which stores schematic representation of objects encountered in the environment. Another module could store the auditory name associated with the concept. For instance, when we hear the word “car” the auditory ART module recognizes the incoming auditory pattern as a word describing a concept of the CAR. Therefore, the activated F2 node in the auditory ART module sends excitatory activation to other ART modules that encode other features of the same concept. For instance, it could activate the visual ART module that encodes the shape of the car, or the typical motion or color of the car. Here, we will consider only the visual ART module that encodes motion described in a sentence. Therefore, when we hear a word and recognize it as a specific concept, a single F2 node in the auditory module is active and provides input to the visual ART module. We do not simulate auditory module

explicitly because it only serves here as an input to the visual ART module the dynamics of which is studied in detail.

Formal specification

Network dynamics in the layer, $n = \{F1, F2\}$, is described using competitive shunting formalism

$$\tau_M \frac{dx_i^n}{dt} = -Ax_i^n + (B - x_i^n)I_i^n - (C + x_i^n)J_i^n \quad (1)$$

where, τ_M , is the time constant for integration A , is a parameter that controls the passive decay toward resting state (or activity leakage), parameter, B , defines the upper activity limit, and, C , defines lower saturation point for the cell activity. Therefore, the node's dynamics is constrained in the interval $[B, C]$. Total excitatory (inhibitory) input to the cell is given by, I_i^n (J_i^n). A node's output is rectified before it can influence other nodes in the network with $y_i = \max(x_i, 0)$.

Mechanics of the activation and signal propagation in the ART could be described as follows. Sensory input is registered at F0 and transmitted to F1. Activation of the F1 layer nodes, x^{F1} , is described by their total excitatory input

$$I_i^{F1} = x^{gain} (y_i^{F0} + \sum_j w_{ji} y_j^{F2}) \quad (2)$$

and total inhibitory input,

$$J_i^{F1} = \sum_{j \neq i} y_j^{F1} \quad (3)$$

F0 is not explicitly represented in the model. Instead, the steady-state activity of the F0 layer, denoted as, y^{F0} , is present in the equation for the F1 nodes and in the equation for the reset node. Vector, y^{F0} , may assume only two values, 1 if that particular motion is present in the visual field or 0 if it is not. Term, x^{gain} , describes the influence of the gain control node which is described below. F1 is also influenced by the F2 nodes through the pattern of top-down synaptic weights, w_{ji} , from the j^{th} F2 node to the i^{th} F1 node.

The activation from F1 layer is transmitted to F2 through a filter of bottom-up synaptic weights, w_{ij} . F2 nodes, y^{F2} , compute a similarity measure between the sensory pattern registered at F1, y^{F1} , and bottom-up weights, w_{ij} , as it is described in the excitatory component of the cell's activation

$$I_i^{F2} = z \left(\sum_j w_{ij} y_j^{F1} + y_i^{F2} + y_i^{F2au} \right) \quad (4)$$

F2 nodes are also driven by the self-excitation, y_i^{F2} , and input from another (auditory) ART module, y_i^{F2au} , which induces perceptual simulation. Detailed justification for this type of connection is given below. In order to simulate adaptation after prolonged exposure to the sensory pattern, we introduce the term, z , which gates the total excitatory activity to the F2 nodes. When the network is in the simulation mode, z is a constant with value 1 because activity level is low and there is no adaptation in the amount of transmitter release. However, when the network spent certain amount of time in the perception mode, z , is temporarily switched from 1 to 0 in order to simulate sensory adaptation, that is, reduced responsiveness of the node due to the exposure to the prolonged stimulation. Such process reduces activity of the winning node and enables transition to the simulation mode. It should be noted that sensory adaptation occurs only during the perception mode because, only in this case, nodes' activity is so strong to produce lack of available neurotransmitter. In the simulation mode, node's neurotransmitters recuperate and reinstate full capacity for signal transmission. Sensory adaptation enables simulation of the empirical evidence that perceptual simulation is disrupted if it is preceded by the perceptual experience which matched with the content of the simulation (Kaschak *et al.*, 2005).

Inhibitory component of the F2 node activity is given by

$$J_i^{F2} = \sum_{j \neq i} \omega_{ji} y_j^{F2} + y_i^{F2} (x^{res} + 1 - x^{gain}) \quad (5)$$

The F2 nodes compete with each other through lateral inhibitory connections and the single F2 node remains active, which represents the best match to the current input. The strength of lateral inhibition from nodes within layer F2 to node, i , is controlled by the synaptic weights, ω_{ji} . The winning F2 node sends top-down signals to F1 layer through a pattern of top-down synaptic weights, w_{ji} , as shown above. Additional inhibitory signals arrive to the F2 layer from the node for reset, x^{res} , and gain the control node, x^{gain} . These signals are modulated by the activity of the F2 node itself. In this way, the reset signal could influence only the active node and all other nodes are left intact. In a similar manner, inverse of the activity of the gain control node, $1 - x^{gain}$, inhibits the target F2 node when the network is in a simulation mode. On the other hand, when the network is in a perception mode, this term vanishes and the node is allowed to attain its maximal firing rate (i.e., B) which leads to a full resonant state.

Finally, F2 output is registered at motor nodes, x^M , which are modeled as leaky accumulator cells as

$$\tau_M \frac{dx_i^M}{dt} = -x_i^M + 2y_i^{F2} + 0.5y_i^M - \sum_{j \neq i} y_j^M \quad (6)$$

Where, τ_M , is the time constant for integration, y^{F2} , is input from the corresponding F2 node, y_i^M , is self-excitation which enables accumulation of evidence and, $-y_j^M$, is lateral inhibition from other accumulator cells. Motor (output) cells generally have slower dynamics with respect to other network elements. Motor neurons are considered to make an overt response when their activity reaches a threshold, T .

Gain control node, x^{gain} , is implemented simply as

$$\frac{dx^{gain}}{dt} = -x^{gain} + 0.1 + 0.9 * I \quad (7)$$

With $I=1$ if perception mode is active and $I=0$ if simulation mode is active. A node for reset signal, x^{res} , is described with

$$\frac{dx^{res}}{dt} = -x^{res} + H \left(\frac{1 - x^{gain} + \sum_i y_i^{F0} y_i^{F1}}{D + \sum_i y_i^{F0}} \right) \quad (8)$$

Where $H(x)$ is a Heaviside function with $H(x)=1$ if $x < p$ and $H(x)=0$ if $x > p$. Parameter, p , is a network vigilance which controls how sharp must the match between the bottom-up activation and the top-down expectation be in order to produce resonance. If the mismatch is greater than allowed by the p , the reset signal inhibits the currently active F2 node and enables another F2 node to become active. Inverse of the gain signal is added here in order to prevent activation of the reset signal during simulation mode. Therefore, reset should be activated only in the perception mode. Pair wise multiplication between vectors y^{F0} and y^{F1} enables computation of the match between the sensory pattern and the top-down expectancy pattern. Parameter, D , is a small constant which prevents infinite growth of the ratio in eqn 8.

The ART family of networks is primarily designed to explain properties of category learning in non-stationary environment (Carpenter & Grossberg, 2003). Here, we were focused on the dynamical aspects of the network behavior and we do not explicitly model learning. That is, we assumed that appropriate connection weights were learned in advance and in computer simulations they are supplied as a fixed set of parameters.

Simulation

In order to illustrate the network behavior we numerically solved equations 1, 6, 7, and 8 using 4th order Runge-Kutta method. Parameters were set as follows: $A=.1$; $B=C=I$, $D=.1$; $p=0.6$; $\tau=2$; $\tau_M=10$; $\omega_{ji}=2$ for all i and j , $T=2$ if the network entered into the perception mode or $T=0.5$ if the network entered into the simulation mode for all nodes in the motor layer. Network behavior is robust with respect to

the parameter changes because crucial network components such as the gain control and reset nodes produce qualitatively distinct signatures on the network output. All network layers contained two nodes. Bottom-up and top-down connections between F1 and F2 are given by

$$w_{ij} = w_{ji} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}. \quad (9)$$

One node encodes motion toward the observer and another node for the movement away from the observer. The sensory layer (F0) could be considered to reside in the MT or MST cortices which are known to be involved in perception of global movements. First we will consider how perceptual simulation influences perceptual decision in a simple condition of discriminating between movement toward the observer or away from the observer.

During auditory presentation of a sentence as in the experiment of Zwaan *et al.* (2004), category nodes in F2 layer of the auditory ART module are activated in response to words in the sentence. This activation triggers perceptual simulation in the visual ART module containing nodes for movement (toward and away). Perceptual simulation activates F1 nodes corresponding to simulated motion (e.g., motion mentioned in a sentence) via top-down connections from F2 to F1 in the visual ART module. It should be noted that visual ART module is in a simulation mode which means that its gain control mechanism disables F2 nodes from reaching their maximal activity amplitude. On the other hand, auditory ART module is in a perception mode because it directly perceives a pattern of sounds corresponding to spoken words. Perceptual simulation is distinguished from direct perception by the activity level of the nodes within a specific ART module.

Results

In the sentence “The shortstop hurled the softball at you” there is implied motion of the ball toward the observer. If the sentence is followed by a picture of the ball moving toward an observer, the response to the ball motion will be faster compared to the presentation of the ball moving in the opposite direction. Figure 2A and 2B illustrates this difference. Perceptual simulation starts at $t=0$ after hearing the sentence. At $t=30$ motion stimulus in one of two directions is presented to the network, that is, one of the x^{F0} nodes is set to 1. At the same time, network enters the perception mode by switching the x^{gain} from 0.1 to 1.

When there is a mismatch between the motion direction mentioned in the sentence and the actual movement (fig. 2A), a reset signal is issued to the F2 layer which inhibits the currently active F2 node. After that, another F2 node is activated based on the sensory input alone. However, due to the fact that erroneous F2 node was active for a certain period of time, F2 node encoding the correct motion will need more time to achieve resonance. This is evident in the

activation of the motor output nodes which integrate signals from F2 nodes.

On the other hand, when there is a match between F2 and F0 layers there is no need for a reset and the correct F2 node is activated and starts to resonate in a shorter period of time (fig. 2B). This is reflected in the output layer as a faster response or faster threshold crossing for the initiation of the motor response. If the spoken sentence implied opposite motion like in “You hurled the softball at the shortstop” neural dynamics of the nodes for the perception of movement (toward and away) would exhibit opposite trajectories.

The opposite pattern of results arise if perception precedes simulation as in experiment of Kaschak *et al.* (2005). In this case, motion is perceived before the simulation starts and the task for the participant is to judge the sensibility or grammaticality of the sentences. When the sentence “The car approached you” is presented, the sensibility judgment will be faster if it is preceded by a motion in an opposite direction (away) rather than in the same direction as implied by the sentence (toward). A possible reason for this effect is sensory adaptation, which desensitizes currently active nodes so that they will be less responsive to repetitive stimulation.

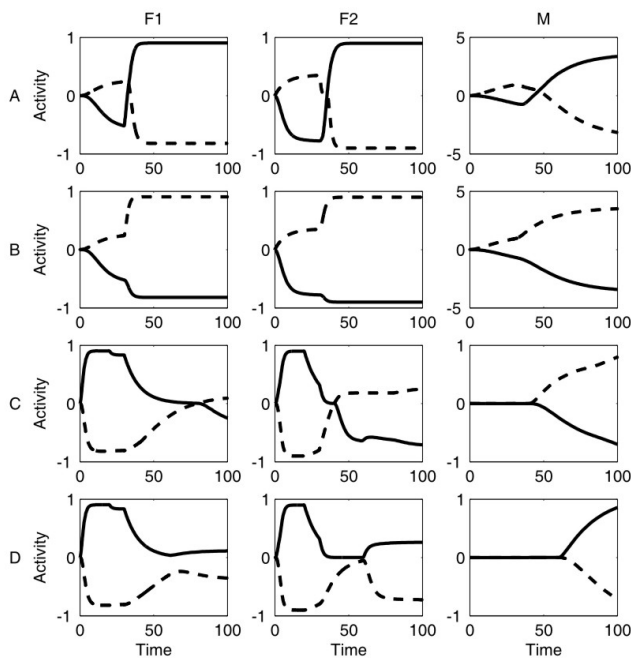


Figure 2. Neural dynamics of perceptual simulation in the mismatch and match condition. When perceptual simulation precedes perception, mismatch condition (A) prolong the reaction time compared to the match condition (B). When perception precedes simulation, mismatch condition (C) produce shorter reaction time when compared to the match condition (D). Solid line – motion away from the observer; dashed line – motion toward the observer.

We implement adaptation as a reduction in neurotransmitter release from F1 and F2 nodes which temporarily disable activation of F2 node responsible for

encoding the perceived motion. Therefore, if the sentence requires simulation of the motion toward the observer and we simultaneously perceive motion in the same direction, the time needed to construct simulation and to reach decision will be longer compared to a situation where the perceived and the simulated motions are different (compare figure 1C and 1D). Of course, the time to recuperate from the adaptation for F2 nodes is set arbitrary and it is possible that the recuperation from the adapting state lasts shorter than required by this computer simulation. However, it should be mentioned that there are other ways in which active F2 node could be silenced after the network enters the simulation mode. For instance, it is possible that an inhibitory signal from the gain modulation node to the F2 nodes is much stronger at the beginning of the simulation which will disable rapid development of simulation when the same node is previously used in perception.

In the simulations C and D we did not use separate motor neurons to represent decision about sensibility of the sentence. We assumed that the sensibility judgments are directly related to the activity of F2 nodes for motion perception. During perceptual simulation these nodes will be active and contribute to the accumulation of evidence that the sentence is sensible. On the other hand, lack of activity in the visual ART module could contribute to the accumulation of evidence that the sentence is not sensible. We can speculate that nodes for the sensibility judgment operate in a similar manner as the nodes for the movement preparation, that is, they will integrate input signals until they will reach threshold. Therefore, if the perceptual simulation starts earlier in time in the visual ART module, it will also speed up decision of the sensibility of the sentence. Of course, in the real sentence comprehension, other attributes are also present and utilized for the construction of meaning. All these perceptual attributes might also have their corresponding ART module which will simulate or reactivate perceptual traces associated with their category or F2 nodes. Such distributed activation across different ART modules which converges toward nodes for the sensibility judgment might be considered as a simplified construction of the meaning of the sentence.

Simulation of the experiment of Zwaan *et al.* (2004) depicted in figure 2A and 2B raised a concern regarding the difference between the simulated motor output and the response made by the experimental subjects. In the model, the response indicates whether there is a movement toward or movement away from the observer. On the other hand, in the experiment, subjects were instructed to check whether two objects presented sequentially were the same or different. The model could simulate this task by introducing a separate ART module for shape analysis. This module would compare two objects by processing first object and after its disappearance; corresponding F2 node would make a prediction regarding the shape of the second object. Prediction will be observable in the pattern of activity across F1 layer which will be compared to the sensory data when the second object appears.

How such comparison unfolds in time in the F1 layer is shown in figure 3. T1 corresponds to the presentation of the first object (i.e., outline of the softball). T2 corresponds to the interstimulus interval between the presentation of the first and the second object. During this time window, F2 node encoding softball reads-out its spatial pattern onto F1 layer. Such read-out is modulated by the expected size of the object. If the sentence implies movement away from the observer, expected pattern will be smaller compared to the original shape presented during T1. If the following shape matches with the expectation, decision that the objects are the same will be accelerated (fig 3, top row). On the other hand, if the sentence implied movement toward observer, expectation will not match with incoming sensory pattern (fig 3, bottom row) and the decision that the objects are the same will be slowed due to the lateral inhibition in the F1 layer and the reset signal.

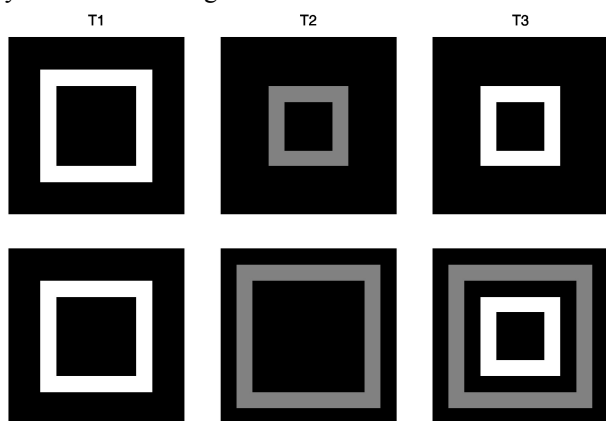


Figure 3. Simulation of the F1 layer of the hypothetical ART module for the shape perception which made object comparison task. T1 – presentation of the first object. T2 – interstimulus interval between object’s presentation. T3 – presentation of the second object.

Discussion

We simulated the differences in reaction time in the shape discrimination task of Zwaan *et al.* (2004) and sensibility judgments in the experiment of Kaschak *et al.* (2005) by using real-time implementation of the ART circuit. Operations of the ART circuit have been used previously to explain a wide range of behavioral, neuropsychological and electrophysiological data (Carpenter & Grossberg, 1993; Grossberg, 1982). The gain control mechanism and reset mechanism enable us to provide mechanistic explanation of why perceptual simulation has a different effect on reaction time in match and mismatch condition and why the reverse pattern of results occur in different experimental settings. In this way, we provide a computational account of how interaction between perception and conceptual processing is achieved by using cortical mechanisms responsible for stable category learning (Carpenter & Grossberg, 2003). Further research will explore the extension of the present approach to the interaction between language understanding

and action planning, that is, simulation of the action-sentence compatibility effect (Borreggine & Kaschak, 2006; Glenberg & Kaschak, 2002).

Acknowledgments

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