Control of Associative Memory During Task Switching (CAM-TS)

CAM-TS was designed to model task switching during the explicit cueing task based on associative memory theories of task switching, such as task set priming (1). As such, other factors such as short-term transient carryover or a time-consuming reconfiguration process, are not directly modeled. The critical assumptions captured by CAM-TS are (*i*) that experience-dependent plasticity strengthens associations among representations active during performance of a given task; and (*ii*) after a task switch, these associations result in facilitated retrieval of competing task-irrelevant information that produces interference and a behavioral switch cost. It is a further goal of CAM-TS to be explicit about the presence and impact of control in resolving such interference due to associative memory processes during task switching.

CAM-TS implements task switching using established mechanisms of connectionist modeling (2), and many of the computational features of this model were adapted or taken directly from other established bias competition models of cognitive control (3-7). Hence, most fundamental assumptions in CAM-TS are those implicit and explicit in any parallel distributed processing system. However, relying on these established computational principles, CAM-TS provides a novel associative account of interference during task switching, and as detailed below, differs from prior similar models (e.g., ref. 6) in that (*i*) there is no short-term carryover of interference from trial to trial, but rather task-switch costs are due exclusively to changes in association weights; (*ii*) endogenous control is implemented explicitly before a task switch; (*iii*) competition occurs primarily not in the goal or task layer but rather among active conceptual representations; and (*iv*) competitors are nondominant, in that without control, the model would not perseverate on the prior task after a switch.

Architecture of CAM-TS

CAM-TS is implemented as a simple parallel distributed processing network (2) (Fig. 2*A*) that consists of three layers corresponding to the Task (Letter and Number), Concept

(Odd, Even, Vowel, and Consonant), and Response (Left and Right) representations in the explicit cueing task. Feedforward connections proceed from the Task layer to relevant units in the Concept layer, and from the Concept layer to the appropriate units in the Response layer. Connection strengths are determined by a set of weights (*w*), such that a higher weight indicates a stronger connection between two units (see Table 1). In this way, activation of a task unit in the Task layer will result in activation of associated Conceptual and Response units, instantiating retrieval of a task set in the model. Likewise, input to the Concept layer due to presentation of a target stimulus will activate the Response associated with that Concept.

Reciprocal feedback connections loop from units in subordinate layers back to superordinate layers. Thus, feedback from active Concept and Response units can activate other associated Concept, Response, and Task units, including irrelevant and so competitive units, a critical feature of interference based theories that emphasize long-term carryover (e.g., task set priming; ref. 1). Finally, within a layer, units are connected via mutual inhibitory connections. This feature renders these layers recurrent, capable of maintaining information in the absence of input (such as during the preparation delay), and further permits a computation of conflict based on the energy in the layer (see below) (5, 8).

Processing in CAM-TS

At the start of a simulation trial, the activation values of all units in the Task, Concept, and Response layers were set to 0, regardless of what occurred on the previous trial, thereby nullifying the possibility of any transient carryover. Presentation of a task cue initiated the first cycle of a trial and was simulated by delivering an input to one of the units in the Task layer and computing activation values across the network.

On each cycle, the net input (*n*) to unit *i*, including external input, was computed according to Eq. **1** (5, 7)

$$n_i = \sum_j a_j w_{ij} s_{ij} + \varepsilon \qquad \textbf{[1]}$$

such that a_j is the positive activation value of the jth input unit on the last cycle, w_{ij} is the weight between the jth input unit and unit i, and s_{ij} is a constant scaling factor that differed only between external (0.4) and internal inputs (0.08). For external inputs, activation values were always 0 or 1, and w and s were determined by the external input weight (0.15) and scaling (see Table 1). The noise term (ε) was distributed normally with a mean of 0 and standard deviation 0.01.

Based on n_i, the change in activation (Δa_i) was then computed according to Eq. **2**:

$$\Delta a_i = \begin{cases} (\psi - a_i)a_i n_i g_i - [(a_i - \gamma)\delta], n_i \geq 0 \\ (a_i - \phi)a_i n_i g_i - [(a_i - \gamma)\delta], n_i < 0 \end{cases} \qquad \textbf{[2]}$$

This equation produces changes in activation equivalent to a logistic function such that as a_i approaches the maximum (ψ) or minimum (ϕ), the influence of n_i diminishes, and a_i tends to decay toward resting activation set by γ at a decay rate determined by δ. The net input (n_i) is scaled by the gain term (g_i), which, when increased, has the effect of making the activation function more sensitive to inputs, and can allow a recurrent network to maintain information in the absence of external input (4). The gain was always uniform across all units of a layer, and unless otherwise noted, gain was set to 1. Computed values of a_i values were further bounded at ψ and ϕ.

External input to the task layer was maintained for six cycles after which external input to the model was ceased and the model was allowed to cycle for a duration of cycles determined by cue-to-stimulus interval (CSI). During this preparation interval, activation in the relevant task unit, along with relevant activation in the associated Concept and Response units, came to dominate. As with the experimental CSI manipulation, variation of CSI used in CAM-TS expanded with a logarithmic schedule setting preparation at 1, 2, 5, and 12 cycles.

Activation of the task set during the preparation interval is enhanced by increasing the gain on the Task layer during the preparatory interval. To simulate a strategic control process coming on-line during a task switch, the gain term in the Task layer was increased to 2.0 during the preparation interval of Switch trials. The dynamics of this control process were such that gain was not increased until after the first cycle of the preparation interval, reflective of the slow onset of control, and was further increased for a maximum of three cycles regardless of the duration of the CSI, after which it was reduced to its default level (1.0).

In its current design, the up-regulation of endogenous control in CAM-TS before a task switch is experimenter-implemented. However, without control, conceptual conflict (see below) and likewise errors by CAM-TS are greatly enhanced, and differentially so for Switch trials. Hence, through experience the system could learn to prospectively associate certain contexts (e.g., Switch trials) with greater conflict/errors or with reduced reward, and so associate these contexts with the need for control (9-11). Likewise, the prefrontal cortex could develop procedural propositions to identify a Switch trial and then to up-regulate control accordingly (12).

After the preparation interval, external input was delivered to the Concept layer, reflecting the presentation of the target stimulus. As with the explicit cueing task, in which both a letter and number are presented as a target, input to the Concept layer of CAM-TS was applied equally to one of the number Concept units (Odd/Even) and one of the letter Concept units (Vowel/Concept). Identification of the target stimuli (such as recognizing the digit “1” as the number one) and its subsequent categorization were not modeled, because these factors were not manipulated in the present theoretical context and so would add little to what is already captured by the scaled external input to the Concept layer.

External input to the Concept layer was maintained for six cycles, after which all external input to the model was ceased, and the model was allowed to cycle until it generated a response, up to a maximum of 100 cycles. A response was recorded once sufficient evidence accumulated in one of the Response units that its activation value exceeded a set threshold (0.25).

On the cycle that a response was emitted, changes in the baseline weight (Δw) for a given input to the Task layer was computed according to Eq. **3** (6).

$$\Delta w_{ij} = a_i a_j \lambda \qquad [\mathbf{3}]$$

such that Δw_{ij} is determined by the product of the activation values (a) of the ith and jth units scaled by the learning rate (λ). In CAM-TS, λ was always set to 1 emulating fast one trial learning. So that weights did not increase indefinitely, changes in weights were always made to baseline weight values rather than to the modified values from the previous trial. This is a simplifying feature of the model and follows others (6) but is not meant as a theoretical position.

Modifying the baseline weights after each trial using this equation has the effect of increasing the connection strengths among units that are conjointly active at the response (i.e., both are active) and diminishing the connection among those Concepts and Responses not conjointly active at the response (i.e., one is active, and the other is not). Hence, when a task switch occurs, associations with competitive representations will have been strengthened by the previous trial, and associations with relevant representations will have been weakened. Because this is a modulation of connection weights rather than activation values, this feature of the model is intended to reflect experience-dependent plasticity in long-term representations and pathways.

After emission of a response, the gain in all layers was dropped to 0.5 to allow information to decay. This is reasonable, because it is not likely that subjects continue to actively maintain the task, target, or response after a button press.

Simulation of Response Time (RT) and Conflict in CAM-TS

The conversion of cycles to simulated RT used identical parameters to those estimated in the context of other control tasks (5, 7) and was based on Eq. **4**.

$$RT = \alpha + cycles \cdot \rho \qquad [\mathbf{4}]$$

The constant value α is meant to capture early perceptual processes not modeled by CAM-TS and was set at 200 ms for all simulations. The cycle conversion rate (ρ) was set at 16 ms for all simulations.

Eq. **5** determined the magnitude of conflict in each layer on any cycle *c* based on the integrated computation of energy (*E*) within the active portion of each layer (8).

$$E(c) = -\sum_{x=1}^{c}\sum_{i}\sum_{j} a_{ix} a_{jx} w_{ijx} \qquad [\mathbf{5}]$$

Energy (*E*) was thus computed based on the sum across cycles of a trial (c = 100) of the sum of the products of the activation values (*a*) in the *i*th and *j*th units of a given layer weighted by their connection strength w_{ij}. Only units with activation values ≥0 were included, because this reflects conflict specifically among retrieved representations. As has been noted previously (5), computational features of Hopfield energy correspond to desirable characteristics of conflict (13), in that energy will increase with increases in activation levels and number of active representations.

As discussed in the text, the association between the response conflict signal computed from CAM-TS and the ramping response in inferior parietal cortical activation was intriguing. Recent evidence from single-unit recordings in posterior parietal cortex (LIP) of the macaque during a motion discrimination task suggests that activity of neurons in parietal cortex reflects accumulated evidence for a given response decision (14). Motivated by this observation, we recalculated the response conflict signal based on accumulated evidence in the Response layer, according to Eq. **6**.

$$E(c) = -\sum_i \sum_j \sum_{x=1}^{c} a_{ix} \sum_{y=1}^{c} a_{jy} w_{ij} \qquad \textbf{[6]}$$

Hence, conflict based on accumulated activation in the Response layer was computed based on the sum of the products of the activation values (a) in the ith and jth units of a given layer integrated across cycles of a trial (c = 100) and weighted by their connection strength w_{ij}. We should note that integration across a trial in CAM-TS is being performed on discrete values at each cycle (e.g., a_x), and so integration is equivalent to summation.

CAM-TS was programmed in MATLAB (Mathworks, Natick, MA) and run on a Macintosh G4 computer. Where parameters were not taken directly from previously established models, parameters were either set by hand or were optimized using a cost minimization algorithm (15) that searched the parameter space. As a source of independent output criteria for use with the algorithm, we used the basic switch versus repeat RT and error costs from Experiment 1 of Rogers and Monsell (16). Hence, parameters were set before simulating the data for Experiment 1 from the present study. Once parameters were set, they were fixed for all subsequent simulations. Simulations of Experiments 1 and 2 were based on 50,000 trials per CSI condition.

Global Preparation and Errors

A variant of CAM-TS might include control that increases on both Switch and Repeat trials (rather than only on Switch trials as implemented in the reported simulations). In CAM-TS, instantiation of global preparation results in a decrease in switch costs over CSI, further demonstrating the advantage of prospective control, but the decrease is considerably more linear (Fig. 5) than the log decrease evident from Experiment 1.

We note that the linear decrease due to global preparation appears to roughly fit the decrease in RT cost from the functional MRI (fMRI) experiment. Although the signature of conceptual conflict does not change qualitatively with global preparation, and so this does not undermine our central arguments regarding a preparatory control process, this raises the possibility that some subjects may have adopted a more general preparatory strategy in the fMRI experiment. This strategy difference may be due to the procedure used in the fMRI for varying CSI. Whereas in the behavioral experiment, CSI could be fully blocked, in fMRI, deconvolution required a different CSI between the first event in a task pair and the second event. Under such variable preparation intervals, switch cost declines can be difficult to obtain (16), and so uncertainty regarding preparation time might result in strategy differences in the application of control by subjects.

Errors have not, to date, been a major focus in the task-switching literature, perhaps because they do not lend themselves easily to interpretation in terms of time-consuming processes along serial information processing stages. Nevertheless, task-switch costs in errors are evident and also tend to decline with increasing CSI. Errors in CAM-TS, as with other bias competition models (7), arise entirely from the noise term, which, in addition to making the model nondeterministic, also can produce loss of information and even slips of action if chance pushes activation values too high too quickly and in the wrong Response unit, before evidence has had time to accumulate in the appropriate Response unit.

Qualitatively similar to error costs reported in the task-switching literature, a higher proportion of Switch than Repeat trials in CAM-TS produced an error. Furthermore, this error cost declined with increasing CSI (Fig. 5). Furthermore, over the first three CSIs, errors declined overall, similar to what is observed in human subjects. However, at the longest CSI, errors increased for Switch and Repeat trials. It is important to note that the Switch versus Repeat error difference still decreased at the longest CSI, indicating that the critical decline in switch RT cost was not due to the model trading speed for accuracy differentially at longer CSI. However, the rise in errors at the longest CSI is likely due to the fact that, at longer retention intervals, there is a greater probability that the noise term will artificially enhance activation values in irrelevant units. This may suggest that up-regulation of gain may need to adjust to longer retention intervals.

A "Selection" Process in Ventrolateral Prefrontal Cortex (VLPFC)

To draw a direct link between the left mid-VLFPC region highlighted presently and that implicated by prior studies of selection from memory, the effects of CSI on neural switch costs was tested in a mid-VLPFC region of interest (ROI) (~BA 45; –54 21 12) previously implicated in resolving interference due to automatically retrieved, but irrelevant long-term associations (17). Consistent with the pattern observed in mid-VLPFC based on ROIs from the current dataset, the magnitude of the neural switch cost in this independently defined mid-VLPFC ROI showed a decline with CSI, evident in a greater Switch versus Repeat difference at the shortest (250 ms) relative to longest (1,150 ms) CSI [$F(1,9) = 4.3$, $P < 0.05$]. Hence, in an ROI derived from an independent study of a postretrieval selection process, we observed a sensitivity of mid-VLPFC to the CSI manipulation as predicted by CAM-TS.

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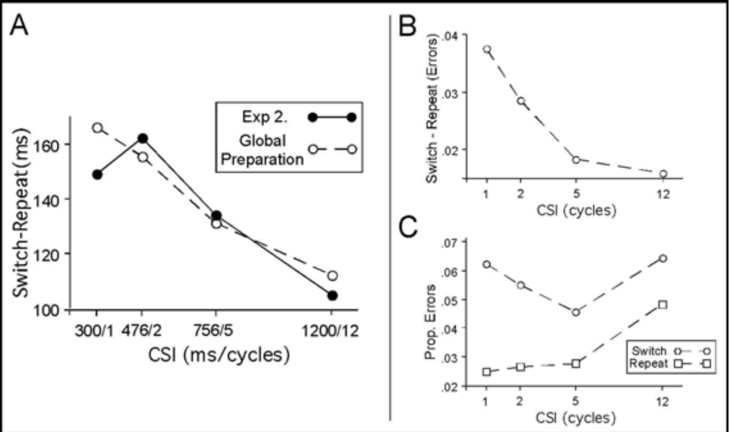
Table 1. Summary of parameters in CAM-TS

Parameter	Value	Interpretation
Task to Concept *w*	2.2	Feedforward projection from Task nodes to relevant Concept nodes
Concept to Response *w*	1.5	Feedforward projection from Concept nodes to linked Response nodes
Concept to Task *w*	1.7	Feedback projection from Concept nodes to Task nodes
Response to Concept *w*	0.2	Feedback projection from Response nodes to Category nodes
Response to Task *w*	0.5	Feedback projection from Response nodes to Task nodes
Task to Task *w*	-3.7	Mutual inhibitory connection in Task layer
Concept to Concept *w*	-1.0	Mutual inhibitory connection in Concept layer
Response to Response *w*	-1.5	Mutual inhibitory connection in Response layer
External input to Task *w*	0.15	Weight on external input to the Task layer
External input to Concept *w*	0.15	Weight on external input to the Concept layer
Internal scaling *s*	0.08	Scales product of input activation and weights
External scaling *s*	0.4	Scales external input
Response Threshold	0.25	Threshold for Response nodes at which response is recorded
Decay Rate Π	0.1	Controls rate at which activation values decay to resting
Max activation Π	1.0	Maximum activation value
Min activation Π	-0.2	Minimum activation value
Rest Π	-0.1	Resting activation value
Noise Π	0.0	Mean of noise distribution
Noise SD	0.01	Standard deviation of noise distribution
Default *g*	1.0	Default gain term
Preparation *g*	2.0	Increased preparatory gain term to up-regulate control
Learning rate Π	1.0	Post-response learning rate for weight modification


A
Switch-Repeat (ms)
160
140
120
100
300/1
476/2
756/5
1200/12
CSI (ms/cycles)
Exp 2.
Global Preparation
B
Switch - Repeat (Errors)
.04
.03
.02
1
2
5
12
CSI (cycles)
C
Prop. Errors
.07
.06
.05
.04
.03
.02
1
2
5
12
CSI (cycles)
Switch
Repeat