Task artifacts and strategic adaptation in the change signal task

Action editor: Nele Rußwinkel
L. Richard Moore Jr. a,*, Glenn Gunzelmann b

a L3 Communications, 5950 East Sossaman Road, Suite 121, Mesa, AZ 85212, USA
b Cognitive Models and Agents Branch, Air Force Research Laboratory Wright Patterson Air Force Base, OH 45434, USA

Available online 7 January 2013

Abstract

The change signal task is a variant of a two-alternative forced-choice (2AFC) task where the initial stimulus is superseded with the alternative stimulus (the change signal) at a delay on a proportion of trials. Taking advantage of the overlap in task requirements, we present a single model that can perform both tasks, and we validate the model using the empirical data from participants who performed them sequentially. The results confirmed the existence of a dynamic hedging strategy in the change signal task, and provided evidence against a role for cognitive fatigue in producing the slower response times with increased time on task. When fitting the 2AFC task, the model required adjustment to one architectural parameter while the rest were left to defaults. That parameter was then constrained while fitting the remaining three task-specific parameters for the change signal task. This effectively reduced a degree of freedom in the model fitting process, and increased confidence in the model as it closely matched human performance in multiple tasks.

© 2013 Elsevier B.V. All rights reserved.

Keywords: ACT-R; Change signal; Two-alternative forced-choice; Cognitive model

1. Introduction

An established cognitive architecture (Anderson, 2007; Meyer & Kieras, 1997; Rosenbloom, Laird, & Newell, 1993) provides the software framework to constrain a model to theories of cognitive processes that have been validated independently in the literature. With an active user community, these unified theories are constantly challenged as modelers increase the breadth and depth of explanatory coverage. As success stories accumulate over time, so does the confidence in the theoretical framework behind the cognitive architecture.

The idea of stressing theories to build confidence can be extended to the models themselves by validating the sub-tasks within the model independently. For example, Myers (2009) reports on a composite model that integrates two previously published models to perform a more complex task. Salvucci (2010) has integrated at least three tasks into his “cognitive supermodel” and calls for more. Independent validation of each sub-task instills greater confidence in the composite model.

In this paper, we present a single model that can perform two tasks with the same set of knowledge and consistent parameter settings. Model performance on the simpler task relies entirely on a subset of knowledge from the more complex task. Because of this relationship, the simpler model can be fit to empirical data, and we would expect any relevant architectural parameters to be identical for the complex task when fitting performance of the same participants on both tasks. Even though the complex task introduces several task-specific parameters that require fitting, all architectural parameters are constrained by the simpler task fit.

The change signal task (Brown & Braver, 2005) and a two-alternative forced choice task (2AFC) provide the context for the empirical study as well as the model discussed in this paper. The change signal task was originally devised by Brown and Braver (2005) as a variation of the classic Logan and Cowan (1984) stop signal task. Whereas the
stop signal task focused on response inhibition, the Brown and Braver variant focused on changing responses. The 2AFC task is the simpler of the two, yet it provides all the necessary fundamentals to perform the more complex change signal task. (There is, however, a parameterized difference in strategy between the two tasks that is discussed in the model fitting section below.)

In Moore, Gunzelmann, and Brown (2010), we examined the Brown and Braver (2005) data and found two interesting characteristics that motivated the study described in this paper. The first was that participants tended to respond more slowly over time, which raises the possibility of fatigue effects due to time on task (c.f., Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2010). However, we will demonstrate that this is not the case for the change signal task, and present a model that shows a similar slowing effect by employing a “hedging” strategy.

Brown and Braver (2005) also concluded, partly on the basis of fMRI data and their neural network model, that implicit learning occurred during the course of performing the experiment. However, in this paper we will demonstrate that implicit learning is not necessary to account for the results equally well.

2. Method

2.1. Participants

Participants included 33 individuals between the ages of 18 and 50, with 18 females and 15 males from the community of Mesa, Arizona. Participants gave written informed consent, and were paid for their participation.

2.2. Stimuli

Each participant performed both the 2AFC task and the change signal task (order was counterbalanced). Both tasks were presented on a computer terminal in a quiet room with minimal distractions.

In the 2AFC task, participants respond to arrows pointing right or left by pressing the associated arrow key on the keyboard. The modification for the change signal task is that, on 1/3 of the trials, a larger arrow appears after the initial stimulus, critically timed to conflict with the execution of the initially signaled response. The larger arrow always points in the opposite direction as the original stimulus, and signals participants to inhibit their initial response and instead respond to the change signal.

In Brown and Braver (2005), the timing of the change signal was dynamically adjusted to induce consistent error rates. In addition, the task implemented two change stimulus delays to produce different error rates: a 50% high error rate condition and a 4% low error rate condition. These two conditions were not explained to the participants prior to the experiment, but they were differentiated by stimulus colors (color cue conditions). We replicated this manipulation in our experiment.

2.3. Procedure

Participants were asked to perform both the 2AFC and change signal tasks during the hour-long experiment. The order of the two tasks was counterbalanced across the participants.

At the start of the experiment, participants were shown the following instructions for the 2AFC (see Fig. 1). The instructions for the change signal task were identical, except the following additional item was added to provide direction for the change signals (see Fig. 2).

The task was designed to select cue colors from a set of high contrast color pairs, where one color was bound to each of the two error conditions in the change signal task. Two colors were used for stimuli in the 2AFC as well, but they were not associated with the task dynamics in any way. The software selected a new set of colors for each task and each participant, although the color assignment remained consistent throughout that particular task run.

After reading the instructions, participants were presented with six sample trials for each task. Instructions for each task were redisplayed before the participants performed it, and there was an optional break between the two tasks.

The change signal task consisted of six blocks of 107 trials each. (The trial count was selected for consistency with the Brown and Braver (2005) experiment.) After each block, participants were allowed to take a brief break. A diagram of the possible sequences of events during a trial and their probabilities is shown in Fig. 3. At the start of each trial, a cue was presented in one of two colors, which was associated with either a high error condition or a low error condition. The significance of the colors in the task was not explained to the participants, but they were made aware that there would be two colors, just as in Brown and Braver (2005).

After 1 second, the cue was replaced with an arrow in the same color that pointed right or left. The participant was instructed to respond to this “go signal” with the appropriate arrow on the keyboard. On 1/3 of the trials, a larger arrow pointing in the opposite direction appeared after a brief delay (the “change signal delay,” or CSD). The participant was instructed that, in these circumstances, they should inhibit their initial response and instead respond to

(1) You will be shown an arrow pointing to the right or left.

(2) The arrow will appear in one of these colors:  

(3) Press the matching arrow key on the keyboard.

Fig. 1. On-screen instructions provided to participants prior to performing the 2AFC task.
(4) A larger arrow may appear just after the first arrow. If it does, ignore the first arrow and press the arrow key that matches the direction of the larger arrow.

Fig. 2. Additional line of instructions provided to participants prior to performing the change signal task.

3. Results

All participants completed 642 trials for each task, except one who mistakenly only completed the change signal task. Data from that individual is excluded from the analyses in this paper.

Generally speaking, the results from our experiment were consistent with the Brown and Braver (2005) study (see Fig. 4). The aggregate data for the change signal task shows the expected slowing in reaction time as the experiment progresses. Conversely, the 2AFC task shows slightly improved reaction times over the duration of the experiment when reaction time is regressed against trial index ($b = -0.032, R^2 = 0.00040, F(1,20342) = 82.49, p < .001$). This result argues against time-on-task based declines in cognitive performance as the source of slowing in the change signal task, and supports the hypothesis that participants were strategically “hedging” their response times.

Within the change signal task, an ANOVA with factors of block and error likelihood confirms that the response times between the two error conditions were significantly different, ($F(5,17552) = 62.48, p < .001$), as found in our previous research (Moore et al., 2010). Overall, participants made errors on 34% of the trials in the high error rate condition, and on 5% of the trials in the low error rate condition. (As mentioned previously, the CSD manipulation adopted from the Brown and Braver study was designed to produce error rates of 50% and 4%, respectively.)

A more revealing perspective on these results can be observed in Fig. 5, which presents response times separately for trials where a change signal was presented...
versus trials where no change signal was presented (go condition). The experimental condition permutations then become:

1. go-low: go signal only (no change signal) presented in the low error condition color,
2. go-high: go signal only (no change signal) presented in the high error condition color,
3. change-low: change signal present in the low error condition,
4. change-high: change signal present in the high error condition.

The figure also includes the response times for the 2AFC task. All reaction times are measured from the onset of the go signal. Reaction times are measured from the onset of the go signal.

The figure also includes the response times for the 2AFC task. All reaction times are measured from the onset of the go signal, and results are aggregated across blocks.

Notice that the 2AFC response times are substantially faster than the response times for all conditions in the change signal task. As mentioned previously, our theory proposes that this is strategic; participants are hedging their responses to go signals in order to allow for the possibility of a change signal being presented. Under this account, the go conditions represent the situation where individuals exhaust their hedge time and produce a response. Therefore, the difference between the 2AFC and go condition reaction times (~300 ms) would reflect the mean participant hedge time.

Also notice the disparity between the change-high and change-low conditions in Fig. 5. In Moore et al. (2010) we suggested that implicit associations between stimulus color and error likelihood might explain the disparity. This was also supported by the original Brown and Braver (2005) work, which focused on learned responses to error conditions in the anterior cingulate cortex (ACC). However, if there was learning of this sort, the impact on human performance is unclear because there is no evidence for a difference in RT between the two go conditions ($F(1, 12607) = .12, p = .73$). If participant behavior was affected by learned associations between error-likelihood and stimulus color, we would expect to see some influence in the go trials similar to that seen in the change trials.

Looking at the response time data for go trials in more detail reinforces this position. Fig. 6 shows the response time distributions for the go-low and go-high conditions. A Kolmogorov–Smirnov test shows that there is no statistical difference ($p = .36$) between the response distributions of the two conditions. This provides further evidence that people were not differentiating between the error-likelihood conditions in terms of their behavior, at least not on go trials, and creates more doubt about whether implicit learning played a meaningful role in the task.

Nevertheless, Fig. 5 shows a difference in response times for change trials between the two error likelihood conditions that requires further explanation. Rather than implicit learning, however, our findings suggest that the emergent difference in response times between the change-high and change-low conditions can be understood as an artifact of the task itself. Recall that correct responses to change signals increase the change signal delay by 2 ms in the low error condition and 50 ms in the high error condition. The different step functions lead to change signal delays that tend to be longer in the high error condition than in the low error condition. The impact of this feature of the task design is to artificially inflate response time estimates in Fig. 5 for change trials because the change signal delay is included. The dynamics of the task mean that this artifact is larger in the change-high condition, which influences the disparity between the change-low and change-high conditions.

To demonstrate that change signal delays are driving the difference in reaction times across the two change conditions, Fig. 7 removes the change signal delay from change condition reaction times (i.e. reaction times are now measured from the onset of the change signal for the trials with a change signal). The disparity between the high and low change conditions in Fig. 5 is greatly reduced, which reinforces the position that it is an artifact of the task itself. In
In this analysis, response times are slightly faster in the high error likelihood condition, reversing the trend in Fig. 5. By looking at the data more closely, we find evidence that the remaining discrepancy in the reaction times between the two change conditions is also related to the task design. The left panel of Fig. 8 shows the response time distribution for the change-high and change-low conditions from the onset of the initial stimulus. The figure suggests that the distribution of response times in the change-high condition is being truncated by the 1000 ms time limit, which is measured from the onset of the go signal. The right panel in Fig. 8 reinforces this, showing a substantially higher proportion of lapses in the change-high versus change-low conditions. Under these circumstances, the mean reaction time will not align with the mode, and instead will be lower than expected. In other words, mean reaction times for the change-high condition will be artificially lower because of the truncated distribution of response times contributing to the average. This is precisely the situation suggested in Fig. 7.

Lastly, the data in Fig. 7 show a significant difference in response times (F(1, 25287) = 1380, p < .001) between the 2AFC and the two change conditions, even though the change signal delay has been removed and participants have no incentive to hedge their responses after the change signal appears. These data suggest that the change conditions impose some extra cognitive processing. This is an important consideration for the model, which will be discussed in the following section.

4. Computational cognitive model

The change signal model was developed within the Adaptive Control and Thought – Rational (ACT-R) cognitive architecture (Anderson, 2007). ACT-R is a symbolic production system coupled with mathematically grounded mechanisms that reflect sub-symbolic influences. The change signal model is instantiated within the architecture by supplying knowledge in the form of production rules and declarative chunks. Our model is relatively simple, consisting of only 14 productions.

The following two paragraphs refer to the control flow diagram of the model shown in Fig. 9. At a high level, the critical feature of the model is a strategic delay of its response to the initial stimulus (the go signal) to accommodate the possibility of a change signal (Fig. 9a). As described in the results section, we refer to this as the hedge time. If a change signal occurs during the hedge time, the model generates a response to the larger arrow (a change signal) as soon as it appears (Fig. 9b). If no change signal occurs during the hedge time, the model responds to the original arrow (Fig. 9c). Time estimates are noisy, and are derived using a mechanism proposed by Taatgen, Rijn, and Anderson (2007).

The model will also adjust its hedge time (which is maintained as a slot in the goal chunk) dynamically based on responses to change signals. When a change signal is detected after it has already responded to a go signal, the hedge time is increased in hopes that it will correctly catch the change signal in the future (Fig. 9d). When the model does correctly respond to a change signal, the hedge time is decreased (Fig. 9e).

The 2AFC task is identical to the change signal task except no change signals are ever presented. As a result, the model can perform the 2AFC task unaltered using a subset of the full procedural knowledge; those productions involved with responding to change signals never fire. In Fig. 9, those productions are shown in gray, so the 2AFC task will only exercise the lighter colored boxes. Also note that the hedge time was set to 0 while performing the 2AFC, so the model responded to go signals immediately after encoding them.
As discussed in the previous section, Fig. 7 shows that there is some additional time cost associated with change signal responses in the human data. There are several plausible theories to account for the increased response time when a change signal is encountered. In our model, the delay is attributed to motor control. The model prepares its response to the “go” signal when it is presented. When a change signal is observed, the motor system is reset, and the motor actions for the new response must then be replanned, which adds time to the response process.

4.1. Fitting

There is one architectural parameter with a non-default value in the model, which impacts the performance of the model on both tasks. The parameter is ACT-R’s default action time, which specifies the time required to complete a production cycle in ACT-R. This entails matching productions in memory to the contents of buffers in the model, selecting one of the productions based on a utility computation, and then executing the chosen production. The default time for this process is 50 ms, but we have found that varying this parameter is useful to account for individual differences in reaction times during research on the psychomotor vigilance task (PVT; Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2009).

In addition to the evidence for this parameter as an individual difference parameter, Stewart, Choo, and Eliasmith (2010) have shown that the execution time of cognitive actions may vary as a function of their complexity based upon spiking neuron simulations. Their models have shown that cognitive actions with little information transfer and wide disparities in production utilities will have faster execution times. This is also consistent with our prior research on the PVT where we propose that cognitive cycles are completed more quickly than the default time in ACT-R (Gunzelmann et al., 2010).

Like the PVT, the change signal model requires minimal information transfer among ACT-R buffers, and there is virtually no conflict between production rules, so faster production cycles should be expected. Rather than refitting the 2AFC task independently, we chose to constrain DAT to the value obtained from our work with the PVT (40 ms; Gunzelmann et al., 2010). The resulting model fit is shown by the lowest two lines in Fig. 10. DAT was subsequently held constant while fitting the model with the change signal task.

The remaining parameters only influence performance on the change signal task. They are the initial hedge time, the increase in hedge time when the model detects an error, and the decrease in hedge time when the model correctly responds to a change signal (these are all set to ineffectual values for the 2AFC task). All three parameters are specific to the hedging strategy, which is to say that they are not parameters that are hypothesized to be associated with the underlying architecture, but rather with the knowledge for this particular task. (We also enabled a mechanism to provide some stochasticity to production cycle times, but

Fig. 9. Control flow of the 2AFC task (light boxes) and the change signal task (all boxes).

Fig. 10. Model fits to empirical data for correct responses.
left that parameter at its default value.) To resolve the three dimensional parameter space, we used the Raptor high performance computing cluster at Wright Patterson Air Force Base running our in-house search software (Moore, 2011). The model was then rerun using the predicted optimal values to produce the change signal model results described next.

4.2. Fitting results

The overall RMSD for the block-aggregated data across all five conditions in Fig. 10 was 33.4 ms. The simpler 2AFC task fit the best at 15.9 ms RMSD, while the go-high condition fit the worst, at 50.1 ms.

The model was not very sensitive to the initial hedge time parameter. Its behavior was primarily driven by the hedge-up and hedge-down values, as they are critical to establishing and maintaining the equilibrium between the model and task. The optimal values (27% increase when hedging up, and 6.5% decrease when hedging down) suggest that participants were more liberal with hedging up (waiting longer when an error is detected) than they were hedging down (responding sooner on subsequent trials when a change signal is correctly detected). Furthermore, there was clearly a relationship between the two variables: larger upward hedges could be paired with larger downward hedges to maintain a reasonable fit. A degree of freedom could potentially be reduced if one of the two parameters could be experimentally isolated.

In addition to the reaction time across blocks, there are several other statistics that can be examined to evaluate the model’s performance relative to human participants. The percent of correct responses, the standard deviation in reaction time, and the number of non-responses are three measures shown in Fig. 11. The model’s performance was within the inter-quartile range on all three measures, and it performed particularly well with percent correct and proportion of non-responses.

5. Conclusions

When theorizing models to explain empirical data, it can be difficult to distinguish between physical constraints of human cognition versus strategic adaptation for the task at hand. Howes and Young (1997) called this the “architecture-strategy credit assignment problem.” The psychological refractory period task has been used as an exemplar (Howes, Lewis, & Vera, 2009), because although the evidence superficially suggests a serial bottleneck in cognitive processing, there are other explanations that produce similar behavior dynamics (Howes et al., 2009).

The change signal task presents a new architecture-strategy credit assignment problem: Are the participants hedging their responses over time, or does the data reflect limitations on attention mechanisms? Furthermore, the dynamic nature of the change signal task provides an additional confound: Are participants learning the association between stimulus color and error condition (e.g., Brown & Braver, 2005), or is this an artifact of the task dynamics? A carefully crafted experiment helped to address these questions and informed the model.

In this research effort, comparing participant performance between the 2AFC and change signal tasks helped resolve the architecture-strategy credit assignment question. Response times for the 2AFC were substantially faster and relatively stable across the experimental session compared to the characteristic slowing seen in the change signal task. This indicates that within task fatigue is not primarily responsible for the changes in response times across the session in the change signal task. Instead, these changes appear to derive from the dynamics of the task, combined with strategic adaptations on the part of participants. That is, the data lead us to conclude that participants dynamically adjust their strategic delays to the “go” signal to maximize the opportunity for detecting and responding appropriately to change signals. This informs the model, and justifies the model’s hedging parameters.

As to the question of implicit learning, a close examination of the data showed that the differences in the performance between the two conditions could be traced to differences in the task dynamics. The model was a valuable tool in this evaluation. The model described here shows that a more parsimonious explanation is sufficient to explain human performance on the change signal task.

In addition to constraining model strategy, the dual task/repeated measures design of the experiment also was useful in constraining architectural parameters. Specifically, the DAT parameter was considered independently from the remaining three, because it was the only parameter involved with the 2AFC task. Because the model requires little information transfer among modules and buffers, and the model itself allows for only one matching production at a time, it falls into the “simple” category by Stewart et al.’s (2010) definition, and was therefore expected to operate with a smaller (faster) DAT value than the ACT-R default.

Fig. 11. Secondary measures of fitness in the change signal task. The box and whiskers demonstrate the variation across participants, while the gray star indicates the mean for the model.
This expectation was confirmed, as we were able to constrain the DAT parameter to values obtained from another model for a “simple” reaction time task (Gunzelmann et al., 2010) and accurately capture human performance on the 2AFC task. The remaining parameters, which were all related to hedging while performing the change signal task, were then fit using that constrained value of the DAT. Thus, by leveraging insights from previous model fitting experience, we were able to remove a degree of freedom in the model.

The current model demonstrates the capacity to perform two tasks with overlapping knowledge using a single set of model parameters. In doing so, it inspires confidence in the theory that the model represents. We believe this is well within the spirit of looking beyond a simple model fit for validation.

We are currently working to extend the model in several ways to further validate and generalize the theoretical mechanisms. First, we are working to broaden the tasks that the model performs (similar to Salvucci, 2010) by extending the knowledge to perform the PVT task mentioned previously. We are also examining performance at a finer level of granularity by fitting individual participant data using the same methodology reported here for the aggregate results. Lastly, we intend to examine the necessity and sufficiency of cognitive mechanisms to account for performance under conditions of sleep loss. The objective is to move toward an increasingly comprehensive explanation of human performance in response time tasks, including how performance is influenced by factors that have a moderating effect on cognitive processing and performance.

Acknowledgments

The views expressed in this paper are those of the authors and do not reflect the official policy or position of the Department of Defense, the US Government, or L3 Communications. This research was sponsored by Air Force Office of Scientific Research grant 10RH04COR. The results described here were originally presented at the 11th International Conference on Cognitive Modeling in Berlin, Germany (Moore, Gunzelmann, & Daigle, 2012).

References


